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Investigating spatially autocorrelated consumer preference for multiple ecolabels: Evidence from a choice experiment

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ABSTRACT

This study investigates spatial autocorrelation in consumer preferences for diverse ecolabels, such as certified ecolabel (type I) and non-certified ecolabel (type II). Ecolabels encourage consumers to purchase environmentally friendly products by informing them of production methods, but their impact is still limited. Further exploration of consumer preferences for ecolabels is vital to understand their influences and improve the efficiency of ecolabel policy. Not only the socioeconomic attributes of consumers but also a spatial spillover effect among consumers may influence consumer preferences for ecolabels, but the extent of its influence remains unclear. This study conducted a choice experiment employing multiple ecolabeled rice and obtained spatially structured data. Spatial analysis revealed a positive spatial autocorrelation in consumers' choices, implying that homogeneous behavior would be observed among consumers who are spatially close to each other. This result suggests that consumers in one region would like to purchase ecolabeled rice frequently, whereas consumers in another region would like to decline to purchase it. Therefore, when evaluating the impact of ecolabel policies, ignoring a positive spatial autocorrelation misunderstands the impact of policies. Furthermore, consumers ' preferences are diverse according to the type of ecolabels. Consumers are willing to pay more to certified ecolabels than non-certified ecolabels. This study proposes practical policy implications for more efficient ecolabel policies based on the results.

1. Introduction

In recent years, consumer environmental concerns have increased. Consumers are more interested in environmentally friendly agricultural products. As a result of this change, the consumption of environmentally friendly agricultural products has increased this decade (Willer and Lernoud, 2019). However, because consumers cannot observe environmental friendliness in the market, they can hardly distinguish environmentally friendly agricultural products from non-friendly ones produced by customary farming practices. Therefore, governments and producers use ecolabels to certify environmentally friendly agricultural production and inform consumers about the product's environmental friendliness (Horne, 2009; Roe et al., 2014; van't Veld, 2020). Ecolabels lead consumers to desirable behavior such as low environmental impact consumption or correct information asymmetry (Asioli et al., 2020; Roe et al., 2014). Currently, the ecolabel index reports 455 ecolabels in 199 countries on various products. ("Ecolabel Index," 2021).

Current ecolabel policies do not sufficiently enhance the actual consumption of environmentally friendly products (Horne, 2009; Meis-Harris et al., 2021; Rex and Baumann, 2007; Willer and Lernoud, 2019; Yokessa and Marette, 2019). For example, while the Ministry of Agriculture, Forestry, and Fisheries (MAFF) emphasizes the importance of Japanese organic farming because of its significant environmental positive impacts (MAFF, 2019), the share of organic products for all retail sales was limited to 1.4% of the Japanese market in 2017 (Willer and Lernoud, 2019). In addition to actual consumption, there is little evidence that ecolabels have significantly changed consumers' purchasing behavior (Meis-Harris et al., 2021). Therefore, we should investigate consumer preferences for ecolabels and design ecolabel policies to significantly impact consumers' purchasing behavior and increase the consumption of environmentally friendly products.

However, some issues of consumer preferences for ecolabels still need to be clarified, especially the lack of studies providing policy implications more directly. First, how consumers shape their preferences for ecolabels has not been thoroughly investigated, especially in terms of determinants beyond individual characteristics (Teisl et al., 2008; van't

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Veld, 2020; Yokessa and Marette, 2019). For example, spatial autocorrelation of preferences for ecolabels has not yet been investigated and remains unclear while it is one of the determinants that shape consumers' preferences (Campbell et al., 2009; Czajkowski et al., 2017; Foelske and van Riper, 2020; Glenk et al., 2020; Liu et al., 2020; Sagebiel et al., 2017; Toledo-Gallegos et al., 2021). The spatial autocorrelation of preferences refers to the spatially heterogeneous distribution of preferences, such as the local bias of positive preferences for ecolabels. Analyses that ignore spatial autocorrelation in preference bias estimation results (e.g., individual and aggregate WTP values) overlook the essential aspects of consumer preferences and fail to present practical policy implications. Second, there is a lack of knowledge regarding consumers' preferences for diverse ecolabels, that is, certified and non-certified ecolabels. Both type of ecolabels are different in, for example, easiness of labeling and credibility of information, which generate different consumers' response. Therefore, investigating consumer responses to different types of ecolabels is essential for developing more efficient ecolabel policies (Teisl et al., 2008). Different ecolabel policies impose different costs (e.g., monitoring and production costs) on policy implementers and producers (Horne, 2009). Because more rigorous ecolabel policies require more monitoring and administrative costs, policymakers should be careful about adopting this type of ecolabel policy. Therefore, comparing diverse ecolabels using an analytical framework that explicitly includes them is essential to understanding which type of ecolabel policy is preferred.

This study investigates consumer preferences for ecolabels, taking two perspectives into account: the spatial autocorrelation of consumer preferences and the third-party certification of ecolabel. Therefore, we conducted an online survey to obtain spatially structured data from a choice experiment using diverse ecolabels such as third-party certified ecolabels and non-certified self-declaration ecolabels. Using the collected data, we tested the hypothesis that consumer preferences for ecolabels are positively spatially autocorrelated and evaluated consumer preferences for various ecolabels.

This study contributes to the empirical knowledge of consumer preferences for ecolabels with and without third-party certification. Specifically, this study reveals the spatial autocorrelation of consumer preferences for ecolabels. In addition, consumer preferences for various types of ecolabels have been studied. Improving the understanding of consumer preferences suggests more efficient and effective ecolabeling policies.

The remainder of this paper is organized as follows. The following section provides the background of this study, including a literature review and an explanation of the ecolabels used in Japan. In the next section, we explain the methods used in this study, such as the choice experiment and estimation strategies. Section 4 presents the estimation results, and Section 5 discusses the results and policy implications. The final section concludes this paper and recommends possible future studies.

2. Current situation of ecolabels

2.1. Basic information about the type of ecolabels

The classification of ecolabels provided by the International Organization for Standardization (ISO) is one of the most recognized and accepted classification approaches (Minkov et al., 2020). Ecolabels can be classified into three types according to the definition of ISO (International Organization for Standardization, 2019). The three categories of ISO are defined as Types I, II, and III. Type I ecolabels are certified by a third-party organization, and this type of label is common as ecolabel in previous studies. Type II ecolabels claim "self-declaration" by producers, distributors, and retailers. The term "self-declaration" indicates that producers can inform consumers about the environmental friendliness of their production methods. This type of ecolabel often does not have certification criteria. Therefore, the accuracy of the information communicated by the producer depends on the conscience of the producer. Finally, type III ecolabels, which were not the objective of this study, are reports or assessments of products.

Additionally, other classifications of ecolabels are also proposed. Specifically, the compulsoriness of ecolabels is considered a determinant of ecolabel classification (Horne, 2009; Rubik and Frankl, 2017). However, this approach is only one suggestion and has not practically substituted the ISO's classification (Minkov et al., 2020). Therefore, this study also adopts the ISO's classification.

2.2. Previous studies on consumer preferences for ecolabels

Consumer preferences for ecolabels have been recognized as an essential determinant in the design of ecolabel policies (Meis-Harris et al., 2021; Peattie, 2010; Rex and Baumann, 2007; van't Veld, 2020). Previous studies have evaluated consumer preferences for ecolabels in various regions, such as Europe (Bjørner et al., 2004; Blomquist et al., 2015; Darnall et al., 2018; Janssen and Hamm, 2012; Roheim et al., 2011), United States (Chen et al., 2018; Loureiro and Lotade, 2005; Meas et al., 2015; Onozaka and McFadden, 2011; Teisl et al., 2002; Van Loo et al., 2015), and Asia (Kim et al., 2008; Sakagami et al., 2006; Uchida et al., 2014; Wakamatsu et al., 2017; Yang et al., 2022).

In general, consumers have positive preferences for ecolabels. Consumers are willing to pay price premiums ranging from 13% to 50% for ecolabeled products that claim environmental friendliness (Cecchini et al., 2018). Consumers appear to be willing to contribute to the environment and society by consuming products produced by environmentally friendly methods. Recently, Potter et al. (2021) have reviewed previous studies investigating consumer reaction (i.e., choice, purchase, and consumption) and revealed that 60 of 76 ecolabels positively impact consumer reaction.

Previous studies have also pointed out the critical drivers of consumers that encourage them to purchase environmentally friendly ecolabeled products. This is because investigating the attributes of consumers who respond more strongly to ecolabels helps facilitate targeting policies and enhance environmentally friendly consumption. For example, Janssen and Hamm (2012) have conducted a choice experiment with 2,441 European consumers and an interview survey and reveal that consumers' credibility on ecolabels is one of the critical determinants of consumers' purchasing behavior. Chen et al. (2018) have revealed that the knowledge of genetically modified food affects consumers' willingness to pay by nationwide online survey. Using an online survey with 600 Japanese consumers, Yang et al. (2022) have clarified the positive impact of information about environmentally friendly products obtained from family members or friends on the possibility of purchasing the product. D'amico et al. (2016) have shown the positive influence of environmental awareness on consumers' willingness to pay. In general, previous studies identify the critical characteristics of consumers who respond to ecolabels more strongly, such as age, income, gender, education level, environmental conscience and concerns, health concerns, knowledge of products, and perception of ecolabels (Meis-Harris et al., 2021; Schäufele and Hamm, 2017).

In addition, some previous studies have investigated the impact of organic JAS ecolabel implemented in Japan (see section 2.3 for details). Sakagami et al. (2006) have clarified the positive value of willingness to pay for a vegetable with organic JAS ecolabel. Kim et al. (2008) have estimated the 10% price premium for a food product with organic JAS ecolabel compared to conventional products.

Previous studies have also suggested that consumers' environmentally friendly behavior is not only influenced by their socioeconomic characteristics but also by social and spatial aspects, such as social networks and spatial spillover effects (Axsen and Kurani, 2012; Baum and Gross, 2017; Peattie, 2010; van't Veld, 2020). One study has pointed out the need to investigate social contexts, such as the impact of others on individuals, for a better understanding of people's environmental behavior (Baum and Gross, 2017). Additionally, another study summarized the studies on the spillover of eco-friendly consumption among individuals (van't Veld, 2020). According to van't Veld (2020), we should investigate consumer preferences for ecolabels from a broader perspective beyond focusing on individual characteristics. In particular, investigating the impact of spatial relationships with other consumers on consumer choices can provide direct suggestions for environmental policies such as the ecolabel policy (Mosier and Thilmany, 2016; Rex and Baumann, 2007). For instance, introducing ecolabel policies designed specifically for certain effective regions (i.e., regions where consumers have a favorable preference for ecolabels) can improve policies. Conversely, identifying regions where ecolabel policies are ineffective can motivate the introduction of environmental policies other than ecolabel policies (e.g., providing additional information about the environment).

2.3. Ecolabel policies in Japan

In Japan, MAFF implements an ecolabel called the "Organic JAS label" for agricultural products to provide evidence of organic production methods (Fig. 1). Ecolabeled products are certified by MAFF to be produced by organic methods that do not allow producers to use chemical fertilizers or pesticides (MAFF, 2017). Moreover, the specially cultivated agricultural products label (SCAP label) is another ecolabel for environmentally friendly agricultural products that follows MAFF's other guidelines. The SCAP label requires reducing the amount of applied agricultural chemicals and nitrogen in chemical fertilizers by 50% compared to locally normal usage levels. There is no original design for the SACP label, and each prefecture modifies the design of the SCAP label. Fig. 2 shows an example of the SCAP label in Tochigi Prefecture, Japan.

The organic JAS and SCAP labels have different primary purposes and criteria. While the primary purpose of the Organic JAS label is zero input of agricultural chemicals and chemical fertilizer, the primary purpose of the SCAP label is to reduce agricultural chemicals and chemical fertilizers (MAFF, 2017; Tochigi Prefecture, 2016). In this sense, the Organic JAS label requires a more rigorous certification procedure for several reasons (Table 1). First, the acceptable usage levels of chemical fertilizers and pesticides vary. The Organic JAS label claims to practice organic agriculture, which uses no chemical fertilizers and pesticides, whereas the SCAP label claims to reduce designated chemical fertilizers and pesticides by 50%. Second, the certification processes were different. For the Organic JAS label, producers need to be monitored and examined by a certification organization designated by MAFF. In contrast, producers need to be examined by third-party organizations for the SCAP label, but third-party organizations do not have to be designated by MAFF. Thus, the Organic JAS label is more trustworthy for consumers than the SCAP label (Darnall et al., 2018; Sirieix et al., 2013).

Other agricultural policies allow farmers to declare their environmentally-friendly agricultural practices to consumers as additional consumer information; this is called the self-declaration policy (Table 1). For example, in Tochigi Prefecture, Japan, one form of self-declaration policy, called "eco-farming Tochigi," is practiced (Tochigi Prefecture, 2021). Self-declaration policies are entirely different from certified ecolabels (Type I) because they have no certification or monitoring process for participating farmers or producers. Therefore, participants have the opportunity to inform consumers of the environmental friendliness of production procedures without any certifications. The self-declaration label can be classified as a type II ecolabel based on the standards. Table 1 summarizes the differences among the three ecolabels in terms of the standards and requirements.

Fig. 1. Logo of the Organic JAS Label.
Source: https://www.maff.go.jp/e/policies/standard/jas/, last accessed:2021/12/12.

Fig. 2. The example Logo of the SCAP Label in Tochigi Prefecture.
Source:https://www.pref.tochigi.lg.jp/g04/work/nougyou/seisan-ryuutsuu/documents/rink_t_keihatutirasi1.pdf, Last accessed:2022/04/01.

3. Methods

3.1. Survey design

The online survey was conducted from December 12 to December 19, 2017, on a representative sample of 1448 rice consumers from a web survey monitor of a private survey company, *Nikkei Research Inc.*, in two Japanese regions: Kanto and Kansai. The Kanto region consists of the Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, and Kanagawa prefectures, while the Kansai region consists of the Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama prefectures. Both regions contain urban areas with the most residents and are the largest consumption areas in Japan. However, both regions include rural areas where agricultural production thrives. Therefore, we believe it is possible to collect unbiased statements regarding rice consumption. For these reasons, we chose both regions as study sites.

The survey mainly aimed to evaluate consumers' preferences for ecolabels. The survey included explanations of the Organic JAS label, SCAP label, and self-declaration label based on standard definitions and questions about respondents' interest in agriculture and the environment, including questions about their attitudes toward agricultural and environmental policies and environmentally friendly agricultural products, residential location, choice experiment using residential choice, and questions about their socioeconomic characteristics. In addition, our survey asked respondents to report a 1 km^2 grid to indicate their residence's location on a given map. Using the reported grids, we geocoded respondents' residential locations. A total of 309 respondents refused to provide information on residential location or reported incorrect information (i.e., non-existent grids or grids outside our study area). Therefore, we excluded those respondents and obtained 1,139

Table 1
Differences among the three ecolabels in Japan.

Label	ISO category	Third-party certification	Monitoring	Chemical fertilizers and pesticides use
Organic JAS	Type I	Yes	Yes	0%
SCAP	Type I	Yes	Yes	50% or lower
Self-declaration	Type II	No	No	depending on the producer

valid responses.

3.2. Choice experiment

Our study utilized a choice experiment to investigate consumer preference for certified ecolabels compared to self-declaration and producer information, such as name, photograph, and messages. The choice experiment is one form of conjoint analysis that can elicit respondents' multi-attribute preferences (Louviere et al., 2000). This method evaluates multiple attributes that affect consumers' purchasing decisions. Respondents had to choose their preferred alternatives, and these choices were repeated as a series of choice tasks.

Our choice experiment used five attributes to describe the hypothetical rice, such as rice brand, ecolabel, self-declaration by producer, information of producer, and price per 5 kg (Table 2). We employed Japanese rice for the choice experiment because we attempted to imitate the purchasing situation. Japanese rice is one of the most important agricultural products for Japanese consumers, and this information can influence their purchase decisions in choice situations.

We employed three ecolabel levels for the choice experiment: organic JAS, SCAP, and no label. Both ecolabels have relatively high recognition (MAFF, 2019) compared to the low recognition of other ecolabels in Japan, such as the MSC label (Swartz et al., 2017). Consumers can recognize such labels on the surface of rice packages on the market. Based on Tables 1 and 2, we explained the definitions of the three ecolabels to clarify their differences before the experiment.

For the self-declaration attribute, we used two levels: declared and not-declared. In this study, the declaration was a form of information that rice farmers sent to consumers at almost no cost. In addition, there is no certification of the production method and no monitoring of the producer's behavior for declaration. This is in contrast to the certified ecolabels mentioned above.

We used names, names + photos, names + photos + messages, and no information to describe the four levels of additional information attributes. Producers often provide information about themselves to consumers in actual markets and influence their behavior (Lahne and Trubek, 2014). We did not use specific messages from producers to consumers for message attributes. Instead, we only indicated that the message from the producer to the consumer was appended in the experiment. This is because using a specific message reduces the generality of the analysis results. To evaluate each information's effect on consumer preference in our estimation strategy, we dissolved this attribute into three dummy variables: name, photo, and message (e.g., *Name* = 1 if the producer's name is displayed. See Tables 2 and 3).

We added nine levels for a rice brand attribute to control for consumers' preferences for rice brands. We used the brand attribute consisting of breed and region because rice breed and production region are often combined to "brand" of rice in the Japanese rice market. Japanese consumers who choose rice pay particular attention to its brand, among other rice attributes (Table 5 in Section 4.1). Therefore, controlling for the brand of rice is essential for analyzing consumer choices. We chose eight of the nine brands according to their familiarity with and sales in the Japanese market, and the remainder, mixed rice, was used to reproduce an actual purchasing opportunity. Essentially, all nine brand levels were popular in Japanese grocery stores. Therefore, we believe that we can allow respondents to imagine actual purchasing situations.

Before the experiment, we asked the participants about the price of rice that they often purchase, referred to as *the usual rice price* in our study. We used five different prices in the choice experiment depending on the respondent's usual rice price: 80%, 90%, 100%, 110%, and 120% of the usual rice price (see Table A1 in Appendix). The rice prices in the choice experiment differed for each respondent to emulate their actual purchasing behavior.

We used Ngene software and generated 32 choice sets without duplication, considering D-efficiency (ChoiceMetrics, 2018). D-efficiency is a guideline for generating an efficient choice design. We obtain the D-efficient profile design by minimizing the variance of the estimated parameters and then minimizing the inverse determinant of the Fisher information matrix (see Huber and Zwerina (1996)). We equally divided the 32 choice sets into four versions and randomly assigned the respondents to one of the four versions. Therefore, the choice experiment was repeated eight times for each respondent with different choice sets. Finally, we asked the respondents to select their favorable alternatives from four options: three hypothetical rice and refusal to choose (i.e., "*Do not buy*"). As a cheap talk script, we asked, "*Please answer our questions keeping in mind that the amount of money you have at your disposal will be reduced by the amount of the product you have chosen.*" and repeated it before each respondent's answer for emphasis (Aadland and Caplan, 2003; Carlsson et al., 2005; Silva et al., 2011). Table 3 presents an example of the choice experiment.

Table 2
Attributes, levels, and definitions.

Attributes	Levels	Definitions
Ecolabel	JAS	Organic JAS label is assigned.
	SCAP	Specially cultivated agricultural products label is assigned.
	No label (base)	No labels are assigned.
Self-Declaration	Declare	Farmers have declared their commitment to environmentally friendly farming practices.
	Not-declare (base)	Farmers have not declared their commitment to environmentally friendly farming practices.
Producer's information	Names	The farmer's name is displayed.
	Names + photos	The farmer's name and photograph is displayed.
	Names + photos + messages[1]	The farmer's name, photograph, and messages to consumers is displayed.
	None (base)	No information is displayed.
Rice brand	Brand1	*Koshihikari*[2] rice produced in Niigata Prefecture.
	Brand2	*Haenuki*[2] rice produced in Yamagata Prefecture.
	Brand3	*Akitakomachi*[2] rice produced in Akita Prefecture.
	Brand4	*Akitakomachi*[2] rice produced in Yamagata Prefecture.
	Brand5	*Koshihikari*[2] rice produced in Tochigi Prefecture.
	Brand6	*Koshihikari*[2] rice produced in Ibaraki Prefecture.
	Brand7	*Koshihikari*[2] rice produced in Shiga Prefecture.
	Brand8	*Koshihikari*[2] rice produced in Hyogo Prefecture.
	Brand9 (base)	Mixed rice.
Price/5 kg	Price	Rice price per 5 kg.

Note:[1] In the experiment, specific names and photographs were not shown; only "Names" and "Photographs" were indicated to avoid the effect of gender and age of name and photograph. [2] *Koshihikari*, *Haenuki*, and *Akitakomachi* are rice breeds.

Table 3
An example of the choice experiment.

Attribute	Option 1	Option 2	Option 3	Option 4	Option 5
Ecolabel	JAS	None	JAS	SCAP	*Do not buy*
Declaration	Not-declare	Not-declare	Declare	Not-declare	
Producer's information	Names	Names + photos	None	Names + photos + messages	
Rice brand	Koshihikari: Niigata	Haenuki: Yamagata	Mixed	Koshihikari: Ibaraki	
Price/5 kg	3,500 yen	2,700 yen	2,000 yen	2,500 yen	
Choose the most preferred option	1. ☐	2. ☐	3. ☐	4. ☐	5. ☐

3.3. Estimation strategy

We used hierarchical Bayes estimation of the random parameter logit model with spatial autocorrelation as the estimation model to analyze the spatial autocorrelation of consumer preferences. Bayesian models have some advantages over traditional maximum likelihood methods, such as avoiding the computational difficulties caused by the sample size and handling outliers and heteroscedasticity (LeSage and Pace, 2008; Train, 2009). For Hierarchical Bayesian estimation, we used R software and the package "RSGHB" (Dumont and Keller, 2019).

The Bayesian procedures were as follows (see Train (2009) Chapter 12 for technical details). First, we assume that random utility models can represent a respondent's choice behavior. Consider the utility function

$$U_{njt} = X_{njt}\beta_n + \varepsilon_{njt} \tag{1}$$

where $n \in (1, 2, \cdots, N)$ is the index of respondents,$j \in (1, 2, \cdots, J)$ is the index of alternatives, $t \in (1, 2, \cdots, T)$ is the index of tasks, U_{njt} is the utility, X_{njt} is the band of attributes, and ε_{njt} is the random draws from Type I extreme value distribution. β_n is the coefficient vector of the individual taste parameters. Considering the spatial autocorrelation of β_n, which is assumed to be normally distributed ($\beta_n \sim N(b, \eta)$), we define the spatial autocorrelated taste parameters as in Equation (2):

$$\beta = \lambda \mathbf{W}\beta + b + \eta \tag{2}$$

where $\beta = \{\beta_1, \beta_2, \cdots, \beta_N\}$ is the matrix of the taste parameters, $\mathbf{W}$ is the spatial weight matrix, λ is the estimated parameter of $\mathbf{W}$, b is the estimated individual taste parameter, and η is the vector of random draws from $N(0, \Sigma)$. λ has a value between -1 and 1. If it has a positive (negative) value, a positive (negative) spatial autocorrelation exists in the consumer preference. The positive (negative) spatial autocorrelation was more substantial when the value of *lambda* was closer to 1 (-1). Equation (2) indicates that this study explicitly considered the spatial effect. Solving Equation (2), we obtain the following equation for β:

$$\beta = (\mathbf{I} - \lambda \mathbf{W})^{-1}(b + \eta) \tag{3}$$

Conditional on β_n, the probability of respondent n's observed choice is written as:

$$L(y_n|\beta) = \prod_t \left(\frac{e^{\beta' x_{ny_{nt}t}}}{\sum_j e^{\beta' x_{njt}}} \right). \tag{4}$$

The unconditional probability is the integral of $L(y_n|\beta)$ over all values of β weighted by the density of β:

$$L(y_n|b, \eta) = \int L(y_n|\beta) g(\beta|b, \eta) d\eta, \tag{5}$$

where g(.) is the normal density with mean b and variance η, and $L(y_n|b, \eta)$ is the mixed logit probability.

We consider that the prior distribution of b is a normal distribution with mean zero and sufficiently large variance, η is an inverted Wishart distribution with K degrees of freedom, and each β_n is a parameter along with b and η. Then, using the prior distributions, the posterior distribution of b, η, and $\beta_n \forall n$ can be written as

$$K(b, \eta, \beta_n \forall n|Y) \propto \prod_n L(y_n|\beta_n) g(\beta_n|b, \eta) k(b, \eta), \tag{6}$$

where Y is the entire observed choice and $k(.)$ where is the prior distribution of b and η.

We can obtain draws from the posterior distribution $K(b, \eta, \beta_n \forall n|Y)$ by Gibbs sampling (Casella and George, 1992; Train, 2009). The Gibbs sampling method obtains each parameter conditional on the other parameter, that is, it follows four steps: (1) take a draw $b|\Sigma, \beta_n$, (2) take a draw $\Sigma|b, \beta_n$, (3) take a draw$\beta_n|b, \Sigma$, (4) iterate (1) to (3) to update the prior distribution to obtain the posterior distribution. After repeating the iteration, the resulting value converges. In our Gibbs sampling settings, the first 5,000 iterations were discarded as burn-in periods to eliminate the influence of the prior distribution. We retained every draw after convergence for 5,000 draws from the posterior in each chain. We generated three chains and obtained 15,000 draws from the posteriors.

The spatial weight matrix $\mathbf{W}$ is essential for spatial modeling. This matrix defines implicit spatial contiguity among all pairs of respondents. This weight matrix consists of an element w_{ij}, and each element weighs the degree of the spatial connection. Although this matrix can affect the estimation result, there are no guidelines for choosing the correct spatial weight matrix (Anselin, 2002). Spatial contiguity, Euclidean distance, economic distance, and social networks can be used to create a spatial weight matrix. This study used Euclidean distance to substitute the spatial connection between each respondent, following a previous study (Kostov, 2010). He points out that we can ensure the exogeneity of the spatial weight matrix using the Euclidean distance for the spatial weight matrix.

The procedure for defining the spatial weight matrix is as follows: Using the parcel respondents reported, we calculated the Euclidean distance of every pair of respondents. When respondents i and j were located at the same parcel, we used the expected Euclidean distance under the assumption of a random location with a uniform distribution, $d_{ij} = 0.5214$ (see Appendix for derivation).

The choice of $\mathbf{W}$ is crucial when considering spatial autocorrelation (Kelejian and Piras, 2017; Stakhovych and Bijmolt, 2009). A popular choice for generating a spatial weight matrix is to use the inverse distance raised to some power (Kostov, 2010). We followed his suggestion and created two spatial weight matrices based on inverse distance and inverse squared distance.

4. Results

4.1. Survey results

Table 4 shows the survey results of our valid sample, that is, the socioeconomic characteristics, awareness of certified ecolabels, and opinions regarding the self-declaration label. Fig. 3a a and 3b represent the spatial distribution of the valid sample. The number of valid samples in the 20–29 age group was small compared to the population. This may be attributed to the fact that the target population of this study is rice consumers and does not include the younger age group, whose rice consumption is relatively low. For gender variables, the valid sample reflected the population. Compared to the population, the number of

Table 4
Number of valid respondents (N = 1,139).

Variable	Description	Valid sample		Study site[1]	
		N	%	N (1000)	%
Age (years)	20–29	72	6%	6,976	17%
	30–39	311	27%	7,661	19%
	40–49	301	26%	9,762	24%
	50–59	225	20%	8,853	22%
	60–69	230	20%	7,268	18%
Gender	Male	601	53%	31,569	49%
	Female	538	47%	32,635	51%
Income (Million JPY)[2]	−2	90	8%	3,254	12%
	2–4	222	19%	7,591	28%
	4–6	240	21%	5,948	22%
	6–8	219	19%	4,110	15%
	8–10	164	14%	2,485	9%
	10–12	85	7%	1,481	6%
	12–14	39	4%	771	3%
	14–	75	7%	1,238	5%
Kanto Region	Ibaraki	1	0%	2,908	7%
	Tochigi	0	0%	1,955	4%
	Gunma	0	0%	1,958	4%
	Saitama	97	13%	7,394	17%
	Chiba	111	15%	6,323	15%
	Tokyo	346	47%	13,844	32%
	Kanagawa	182	25%	9,220	21%
	Total	737	100%	43,602	100%
Kansai Region	Shiga	22	5%	1,419	7%
	Kyoto	54	13%	2,531	13%
	Osaka	193	48%	8,840	43%
	Hyogo	101	25%	5,524	27%
	Nara	26	6%	1,345	7%
	Wakayama	6	1%	945	5%
	Total	402	100%	20,602	100%
Have you ever seen the Organic JAS label?[3]	I have seen it	331	29%	–	–
	I have not seen it	673	59%		
	I do not know	135	12%		
Have you ever heard the specially cultivated agricultural products?[3]	I have known it	212	19%	–	–
	I have not known it	847	74%		
	I do not know	80	7%		
Do you think the self-declaration label policy is an effective policy in order to enhance the pro-environmental agriculture ?[3]	Very effective	86	8%	–	–
	Somewhat effective	405	36%		
	Neither effective nor ineffective	350	31%		
	Not very effective	166	15%		
	Not at all effective.	48	4%		
	I don't know.	84	7%		

Note:[1] All data, except income, are for 2021. Income data were available for 2019. [2] In 2017, 112 JPY = 1 USD. [3] Each question was asked after explaining the respective ecolabels. The population and income data sources are from the Statistics Bureau and the Ministry of Internal Affairs and Communications (Statistics Bureau, 2021a,2021b).

valid samples with incomes below 4 million JPY was small. This is related to the fact that fewer young people were included in the valid sample.

Concerning the Kanto region sample, 47% of the valid sample are respondents from Tokyo and are overrepresented (see also Fig. 3a), and respondents from the Ibaraki, Tochigi, and Gunma prefectures were underrepresented in the valid sample. Our result may strongly reflect the preferences of urban residents due to the bias of respondents in the Kanto region. This point is one of the limitations of this study and will be discussed later. In contrast to Kanto sample, we obtained a valid sample similar to the actual population distribution for the Kansai region (Fig. 3b).

Approximately 30% of the valid samples indicated that they were aware of the organic JAS label, whereas less than 20% of the valid samples were aware of specially cultivated agricultural products. Japanese consumers' awareness of ecolabels is generally not very high (MAFF, 2019). MAFF (2019) reports that approximately 30% of Japanese consumers are familiar with the term "Organic," whereas about 60% of them still do not know the existence of the ecolabel indicating "Organic." According to these facts, our valid respondents' knowledge of ecolabels is not different from the Japanese public. Note that 44% of the valid sample indicated that the self-declared label policy was effective.

Table 5 shows the percentage of respondents' statements regarding the importance of rice attributes in their choice. The importance levels were presented on a five-point Likert scale. As discussed earlier, more than half of the respondents assigned substantial importance to the rice brand (i.e., the rice breed and production region). Additionally, about 40% of the respondents considered the attributes of pesticide and fertilizer reduction to be necessary. Moreover, more than 30% of the respondents indicated that they considered the certification label necessary.

Moran's I statistics were calculated to investigate the spatial autocorrelation in the respondents' socioeconomic characteristics and answers regarding ecolabel policies as a potential source of spatial autocorrelation (Moran, 1950). We cannot observe spatial clusters of respondents' socioeconomic characteristics and answers, as shown in Table 6.

4.2. Choice model results

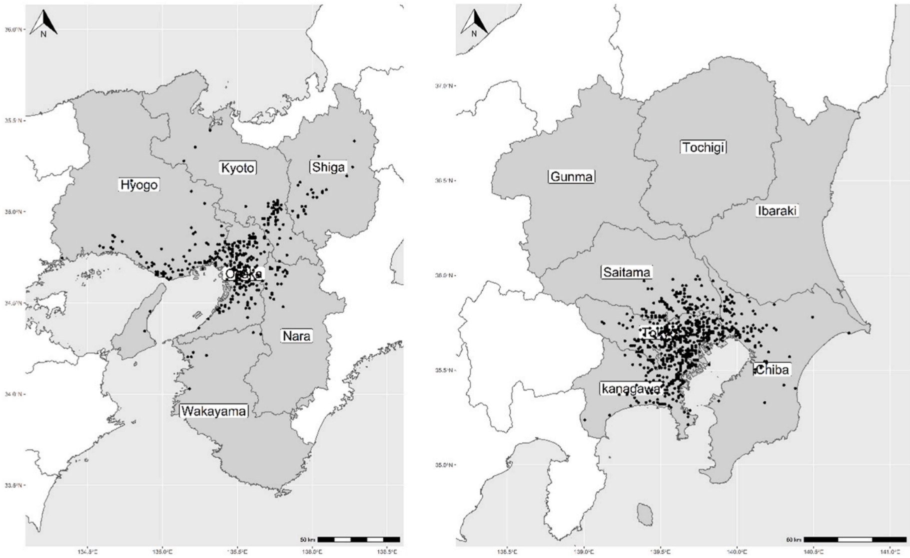
Table 7 provides the three estimation results from the hierarchical Bayes model, with and without spatial autocorrelation. Model (A) was a base model and did not include spatial autocorrelation variables, while Models (B) and (C) did include inverse distance and inverse squared distance, respectively. The three models show similar results, in addition to the *lambda* coefficient. For *Price*, the results show that all models estimate the negative coefficients and do not contain zero in the 95% intervals. This result indicates that, other things being equal, valid respondents prefer less expensive products, which is consistent with the prediction from economic theory.

For two ecolabels variables, *JAS* and *SCAP*, we predicted both ecolabels to be positive and the coefficient of *JAS* to be more significant than *SCAP* because of the difference in the ecolabel requirements. The results show that the coefficients of both labels are positive and do not contain zero in the 95% intervals. These results indicate that ecolabels demonstrate to consumers the environmental friendliness of a product, which increases consumers' willingness to purchase products with ecolabels. In contrast to our prediction, both coefficients are similar for all models, suggesting that the impacts of the two ecolabels on consumers' purchasing behavior are almost identical.

We expected the coefficient to be positive for the *Declare* variables and its value to be smaller than that of the two ecolabels, implying that the self-declaration has positive but limited impacts on consumers. The results show that the coefficient of *Declare* is positive and does not contain zero in the 95% intervals. In addition, the coefficient of *Declare* is smaller than that of the two ecolabels, suggesting that consumers prefer the two certified ecolabels to self-declaration.

For producer information variables, we predicted all variables to be positive because such information is expected to improve the trustworthiness of the producer and encourage consumers to purchase. The results show that the coefficient of *Name* is positive and does not contain zero in the 95% intervals. This result suggests that showing the producer's name on a product may increase consumers' willingness to purchase it. In contrast, the coefficient of *Photo* and *Message* variables contain zero in the 95% intervals, except for *Photo* in the Models (A) and (C). This result does not support the hypothesis that *Photo* and *Message* positively influence consumers' choices, while *Name* positively influences them.

We predicted *lambda* would be positive. The estimation results show



(a) (b)

Fig. 3. (a) Spatial Distribution of Valid Respondents in Kansai Region. (b) Spatial Distribution of Valid Respondents in Kanto Region. Note: The black dots indicate the centroid points of the residence grid, as reported by valid respondents. The same dot shows the respondents who reported the same parcel.

Table 5
Stated importance of rice attributes (N = 1,139).

	Stated importance				
Attribute	5 N (percent)	4 N (percent)	3 N (percent)	2 N (percent)	1 N (percent)
Rice breed	199 (17.5%)	558 (49.0%)	246 (21.6%)	94 (8.3%)	42 (3.7%)
Production region	207 (18.2%)	576 (50.6%)	204 (17.9%)	107 (9.4%)	45 (4.0%)
Pesticide and fertilizer reduction	112 (9.8%)	384 (33.7%)	449 (39.4%)	142 (12.5%)	52 (4.6%)
Certification label	82 (7.2%)	279 (24.5%)	554 (48.6%)	152 (13.3%)	72 (6.3%)
Price	233 (20.5%)	499 (43.8%)	284 (24.9%)	90 (7.9%)	33 (2.9%)

Note: 5 = very important, 4 = somewhat important, 3 = neither important nor unimportant, 2 = not very important, 1 = not at all important.

Table 6
Moran's I statistics of respondent's socioeconomic characteristics and answers regarding ecolabel policies (N = 1,139).

Variable	Moran's I statistics
Age	0.00
Gender (Male = 1, Female = 0)	0.09
Income	0.00
Have you ever seen the Organic JAS label?	−0.06
Have you ever heard the specially cultivated agricultural products?	0.13
Do you think the self-declaration label policy is an effective policy?	0.16

Note: We calculated Moran's I statistics by GeoDa software (Anselin et al., 2010).

that *lambda* is positive and does not contain zero in the 95% intervals for all spatial models, as we predicted. Specifically, *lambda* is 0.37 for Model (B) and 0.38 for Model (C). The values of both coefficients are identical, suggesting that consumer preference is positively spatially autocorrelated.

If the preference for locally produced rice is the cause of spatial autocorrelation, we would expect the effect of the variable to be explained by spatial effects among the latent variables. Thus, the values of the coefficients of the brand dummies are different. However, the results show that the three models estimate similar coefficients for brand dummies, except for *Brand2*. This result suggests that the cause of spatial autocorrelation in consumer preferences is not the rice production area.

Next, the model fit among the models varied. Non-spatial model, Model (A), shows the best model fit compared to both spatial models, Models (B) and (C), considering the values of log-likelihood and Bayesian Information Criteria (BIC) (Wagenmakers, 2007). Model (B) was the best-fit model among the spatial models based on both model-fitting values.

Table 8 presents the estimated mean WTP for the ecolabel variable. Overall, we obtained similar results for all the models. The estimated WTP was 1092 JPY for *JAS* and *SCAP* and 528 JPY for *Declare* in Model (A). Model (B) estimated almost identical WTPs for *JAS* and *SCAP*. The WTPs values were 1,324 and 1,120 JPY, respectively. In contrast, the WTP for *Declare* in Model (B) was greater than that in Model (A) (632 vs. 528 JPY), which indicates that ignoring spatial aspects may underestimates WTPs.

5. Discussions and conclusion

5.1. Positively spatially autocorrelated consumer preferences

Our estimation results reveal that consumer preferences for ecolabels are positively spatially autocorrelated, which is consistent with earlier studies that highlight the spatial autocorrelation of people's environmental preferences (Campbell et al., 2009; Czajkowski et al., 2017; Foelske and van Riper, 2020; Glenk et al., 2020; Liu et al., 2020; Sagebiel et al., 2017; Toledo-Gallegos et al., 2021). Thus, this study supports their suggestion and emphasizes the spatially autocorrelated consumers' environmental preferences.

We suggest two potential sources of positive spatial autocorrelation. Consumers who have similar preferences for environmental goods would decide to live in the same area, which is called spatial sorting (Abildtrup et al., 2013). Residential attributes and preferences for environmental quality influence consumers' housing choices. Thus, people in similar areas may have similar environmental preferences.

Table 7
Estimation results for three models.

Variables	Model (A)		Model (B)		Model (C)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Price (1000 JPY)	−1.60	0.07	−1.70	0.26	−1.86	0.18
	[−1.73 - −1.46]		[−1.97 - −1.21]		[−2.13 - −1.47]	
JAS	1.74	0.08	2.25	0.17	2.06	0.18
	[1.58 - 1.91]		[2.01 - 2.50]		[1.81 - 2.38]	
SCAP	1.75	0.08	1.90	0.27	1.80	0.12
	[1.61 - 1.90]		[1.51 - 2.34]		[1.60 - 2.01]	
Declare	0.84	0.05	1.07	0.11	1.04	0.10
	[0.76 - 0.93]		[0.92 - 1.28]		[0.86 - 1.24]	
Name	0.67	0.05	0.91	0.23	0.74	0.19
	[0.56 - 0.77]		[0.52 - 1.29]		[0.37 - 1.03]	
Photo	0.13	0.04	0.31	0.24	0.39	0.27
	[0.04 - 0.21]		[−0.08 - 0.72]		[0.13 - 1.11]	
Message	0.08	0.04	0.21	0.32	0.22	0.23
	[−0.01 - 0.13]		[−0.30 - 0.70]		[−0.03 - 0.73]	
Brand1	3.01	0.08	3.01	0.35	3.14	0.15
	[2.85 - 3.16]		[2.54 - 3.56]		[2.9 - 3.44]	
Brand2	1.86	0.08	1.38	0.19	1.36	0.10
	[1.71 - 2.01]		[0.93 - 1.72]		[1.12 - 1.54]	
Brand3	2.52	0.09	2.32	0.09	2.58	0.23
	[2.36 - 2.66]		[2.08 - 2.44]		[2.18 - 2.94]	
Brand4	2.37	0.06	2.49	0.31	2.35	0.10
	[2.27 - 2.51]		[2.04 - 3.08]		[2.15 - 2.54]	
Brand5	1.71	0.07	1.45	0.23	1.57	0.12
	[1.58 - 1.84]		[1.06 - 1.78]		[1.31 - 1.76]	
Brand6	1.88	0.10	1.83	0.24	1.80	0.31
	[1.65 - 2.03]		[1.45 - 2.17]		[1.40 - 2.44]	
Brand7	1.69	0.10	1.50	0.30	1.23	0.28
	[1.52 - 1.88]		[1.11 - 2.02]		[0.84 - 1.68]	
Brand8	2.47	0.09	2.34	0.24	2.20	0.09
	[2.31 - 2.63]		[2.06 - 2.80]		[2.05 - 2.37]	
ASC	−0.61	0.09	−0.54	0.07	−0.73	0.10
	[−0.76 - −0.45]		[−0.65 - −0.40]		[−0.92 - −0.49]	
Lambda			0.37	0.15	0.38	0.10
			[0.15 - 0.67]		[0.16 - 0.56]	
Element of **W**			$1/d_{ij}$		$1/d_{ij}^2$	
N of individuals	1,139		1,139		1,139	
N of observations	9,112		9,112		9,112	
Log-Likelihood	−8,024.90		−13,257.33		−14,608.92	
BIC	16,186.56		26,660.54		29,363.72	

Note: S.D. indicates the standard deviation of the estimated parameters. The brackets display the minimum and maximum estimated parameters of 95% credible interval [2.5% - 97.5%]. *Brand9* is the base variable for *Brand* dummies.

Table 8
Estimated mean WTPs (in JPY).

	Model (A)	Model (B)	Model (C)
JAS	1,092	1,324	1,110
	[1,055 - 1,132]	[1,265 - 1,382]	[1,041 - 1,174]
SCAP	1,092	1,120	949
	[1,057 - 1,129]	[1,058 - 1,172]	[916 - 1,035]
Declare	528	632	564
	[504 - 552]	[599 - 656]	[514 - 613]
Name	416	537	395
	[348 - 480]	[308 - 761]	[199 - 555]
Photo	80	180	209
	[25 - 130]	[−48 - 427]	[71 - 598]
Message	49	126	121
	[−5 - 84]	[−175 - 415]	[−16 - 390]

Note: The estimated WTPs values are calculated using the *Price* parameter and estimated parameters. The brackets display the minimum and maximum estimated 95% credible intervals [2.5% - 97.5%].

Considering this possibility in the context of ecolabels, consumers who are favorable to the environment and likely to purchase ecolabeled products will reside in environmentally affluent areas based on their preferences. Thus, people's characteristics may be spatially autocorrelated. However, based on the results shown in Table 8, this study cannot support statistically this potential.

In addition, consumers dwelling in close areas would interact socially. In addition, their behavior may influence neighboring consumers. These interactions are one form of the accustomization effect (Nielsen et al., 2007). People interact with their neighborhoods in daily life (e.g., using the same shops), and such interactions can create social norms. Social interaction or social norms may influence people's pro-environmental behavior and preference for environmental goods (Chen et al., 2015; Farrow et al., 2017; Videras et al., 2012). For example, repeatedly observing a neighbor's purchasing behavior in a store might influence consumers' preferences for ecolabeled products. However, further studies are required to investigate the causality of spatial autocorrelation.

Although the underlying causes of spatial autocorrelation in consumer preferences are beyond the scope of this study and remain a future study, this study highlights the importance of spatial aspects in environmental policy evaluation. Many previous studies investigate the consumer preferences for ecolabels and assess the ecolabel policy without considering spatial aspects, although another study on green consumption stresses the spillover effect across consumers (van't Veld, 2020). For instance, consumers' green consumption may signal their status to others (Griskevicius et al., 2010). As a result, consumer preferences and behaviors may become spatially autocorrelated. Therefore, evaluation of environmental policies such as ecolabel policy without spatial aspects would potentially misunderstand the impact of policies. When evaluating the impact of ecolabels on consumer behavior, it is important to explicitly include the spatial perspective in an evaluation strategy.

The result of model fit (the values of log-likelihood and BIC) indicate that non-spatial model is superior to spatial models in terms of model fit representing by the log-likelihood value. However, this point will not undermine the contribution of spatial analysis in this study because the result of spatial models suggest that the existence of spatial autocorrelation in consumer preferences for ecolabels. Understanding the spatial autocorrelation in consumer preferences for ecolabels allows us to improve ecolabel policies. We will discuss in later (see section 5.3).

Finally, we have to note that this study implicitly assumes that preferences for ecolabels cause positive spatial autocorrelation. Previous studies have suggested several causes of spatial autocorrelation in environmental preferences, such as the spatially heterogeneous distribution of socioeconomic characteristics (Toledo-Gallegos et al., 2021). We discuss this point in the limitations section.

5.2. Consumer preference for certified and non-certified ecolabels

The results suggest that consumers prefer more credible ecolabels that require third-party certifications, which is in line with previous studies (Darnall et al., 2018; Taufique et al., 2014). The estimated coefficients of both certified ecolabels (*JAS* and *SCAP*) were more substantial than that of the self-declaration label (*Declare*) for all estimation models. The WTP for certified ecolabels is 1.8–2.1 times larger than that for the self-declaration label. The results indicate that consumers prefer certified ecolabels to self-declared labels. We speculate that this difference would lie in whether the ecolabels require third-party certification (certified ecolabels) or rely on the producer's conscience (non-certified ecolabels).

However, the results also contrast with previous studies on consumer preferences for self-declaration labels (Dekhili and Akli Achabou, 2014; Fanasch and Frick, 2020) which implies that self-declaration labels are equivalent to or superior to third-party certification labels. This difference would be due to the difference in declaration-agent: small farmers vs. Nespresso, or using data obtained by choice experiment vs. actual price data. Further studies are essential for understanding the impact of self-declaration labels.

It should be pointed out that the results do not imply that self-declaration policies have no effect on consumers and are not worth implementing. Although the impacts are limited compared to certified ecolabels, the findings also imply that farmers' self-declaration would be a valuable signal for consumers (Tables 4 and 8). Table 4 shows that nearly half of the respondents considered self-declaration labels effective in order to enhance the pro-environmental agriculture. The ease of introducing self-declaration policies (e.g., low introduction cost) allows policymakers to implement self-declaration. We discuss the usefulness of the self-declaration policies in the following section.

5.3. Policy implications for ecolabel policies

The results proposes two policy implications. First, according to the results of positive spatial autocorrelation in consumer preferences, tailoring ecolabel policies to the characteristics of local consumers would be effective in increasing their effectiveness. The spatial autocorrelation in people's preferences for ecolabeled products suggests that homogeneous choice behavior based on people's preferences would be spatially aggregated. That is, on average, ecolabeled rice would be purchased more frequently in some regions, whereas people in other regions would decline. Therefore, providing people with more opportunities to purchase ecolabeled products could encourage them. For example, local green markets for agricultural ecolabeled products would work well for local people. In contrast, our study also suggests that people who do not support ecolabeled products live in certain areas. Thus, it would be vital to promote ecolabeled products in areas where people live by providing richer information about the benefits of purchasing ecolabeled products (Borin et al., 2011; Rex and Baumann, 2007). Hence, local governments or NGOs should recognize the availability of localized policies and markets for ecolabeled products and ensure that ecolabeled items are preferred.

Second, multiple ecolabel policies would be valuable for increasing the consumption of ecolabeled products and realizing more sustainable agricultural consumption and even production. Diverse ecolabel policies allow policymakers to meet the demands of both consumers and agricultural producers. As an example, this study proposes the introduction of self-declaration ecolabel policies as well as certified ecolabel policies because self-declared ecolabel policies are expected to serve as a new option for producers to provide information to consumers. Self-declaration-type policies have advantages, such as consumers exhibiting positive WTP, as shown by this study, and lower implementation costs for policy makers and producers than certified ecolabel policies (Yenipazarli, 2015). These advantages not only encourage consumers to purchase ecolabeled products, but also facilitate producer participation in the policy. Furthermore, producers who experience increased demand as a result of policy participation would consider participating in more rigorous policies in the future, such as the Organic JAS label. This study proposes that self-declaration be implemented in a wider area of Japan as a gateway to the Organic JAS label.

However, self-declaration policies have a disadvantage, mainly because of the lack of a monitoring process. This drawback may incentivize participating producers to misrepresent the characteristics of products (e.g., greenwashing). Given this point, further studies of producer behavior under this self-declaration scheme is essential.

5.4. Limitations, future studies, and conclusion remarks

Several limitations and possible future studies of this study should be acknowledged. First, as noted in Section 5.1, this study cannot address the causal relationships between positive spatial autocorrelation and consumer preferences for ecolabeled rice. Causality analysis is essential to understand the causes of spatial autocorrelation and to propose more practical policy implications in future studies. Specifically, we should explore the sources of positive spatial autocorrelation, such as the origin of products, environmental attributes, and individual socioeconomic characteristics (Toledo-Gallegos et al., 2021).

Second, we cannot identify the appropriate area for a localized policy and market. Our results suggest local market availability for ecolabeled products, but we did not reveal the area's attributes and consumers. Examining consumers' locations and characteristics that positively influence demand is essential for creating well-functioning local policies and markets.

Third, this study should be expanded to obtain more generalized results. This study collected respondents from the Kanto and Kansai regions, the most densely populated regions in Japan. However, our valid respondents were concentrated in urban areas in both regions, such as Tokyo and Osaka. As a result, our results may more strongly reflect the preferences of consumers in urban areas, which might cause a bias in the result. Moreover, different countries have different conditions regarding consumption and production, such as the market structure, producers' credibility, information availability, consumer habit, and third-party organizations for certification. These differences would generate a different reaction of consumers to certified and non-certified ecolabels. For example, non-certified ecolabels may not work well in other countries/areas where consumers are not having trust in producers for some reasons because non-certified ecolabels rely on trust between consumers and producers. Therefore, we need to be careful to apply the results of this study to other regions directly, especially where conditions related to consumption are entirely different. Collecting samples from other areas, such as agricultural areas and different countries, is essential for obtaining more robust and generalized results. In addition, other methodologies, such as laboratory experiments, are required to more generalized results.

This study investigated consumer preferences for ecolabels by considering the spatial autocorrelation of consumer preferences and the variety of ecolabel types. This study contributes to the empirical knowledge on consumer preferences for ecolabels. Specifically, this study reveals the spatial autocorrelation of consumer preferences for ecolabels. While some future studies remain, we emphasize contributing to a better understanding of consumers' preferences for ecolabels. Improving the understanding of consumer preferences can suggest ecolabeling policies more efficiently and effectively, which increases consumers' green consumption.

Author contributions

Conceptualization, S.K., M.F., and K.K.; Methodology, S.K., M.F., and K.K.; Formal Analysis, S.K.; Data Curation, S.K., M.F., K.K.; Writing—Original Draft, S.K., Writing—Review and Editing, S.K.; Supervision, M.F., K.K.; Funding Acquisition, K.K.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix

Table A1
Corresponding of Usual Rice Price and Five Rice Prices in Choice Experiment.

Usual rice price (JPY/5 kg)	N	80%	90%	100%	110%	120%
−499	5	399	449	499	549	599
500–999	15	600	675	750	825	900
1000–1499	125	1000	1125	1250	1375	1500
1500–1999	427	1400	1575	1750	1925	2100
2000–2499	261	1800	2025	2250	2475	2700
2500–2999	112	2200	2475	2750	3025	3300
3000–3499	66	2600	2925	3250	3575	3900
3500–3999	19	3000	3375	3750	4125	4500
4000–4499	14	3400	3825	4250	4675	5100
4500–4999	9	3800	4275	4750	5225	5700
5000–	13	4000	4500	5000	5500	6000
I do not know	73	960	1080	1200	1320	1440

Note: We assumed that the rice price would be 1200 JPY if the respondent answered "*I do not know*" for their usual rice price because the average rice price was 1204 JPY in August 2016.

The expected Euclidean distance is derived as the following procedure.

$$P[|X_1 - X_2| \leq x] = 1 - (1 - x)^2 = 2x - x^2$$

$$f(x) = \begin{cases} 2(1-\mathrm{x}) & 0 \leq \mathrm{x} \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\mathrm{E}[d] = \int_0^1 \int_0^1 4(1-x)(1-y)\left(x^2+y^2\right)^{0.5} dxdy$$

$$= \frac{1}{15}\left(2+\sqrt{2}+5\ln\left(1+\sqrt{2}\right)\right) = 0.5214054\ldots \tag{A1}$$

It may be pointed out that the possibility of consumers in the two largest regions, Kanto and Kansai, differs in terms of food consumption preferences. Therefore, the valid sample is divided into Kanto and Kansai subsamples and an exact estimation is conducted to perform a robustness check. Table A2 shows the estimation results from Models (A) and (B) using the Kanto and Kansai subsamples, respectively, and Table A3 shows the calculated mean WTPs. As seen in the results, similar results are obtained for all samples and the estimation with subsamples, suggesting that relatively robust results are obtained using the entire sample.

Table A2
Estimation Results for Subsamples.

	Kansai Subsample				Kanto Subsample			
	Model (A)		Model (B)		Model (A)		Model (B)	
Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Price (JPY 1000)	−1.81	0.09	−1.41	0.25	−1.55	0.08	−1.62	0.11
	[−2.00 - −1.63]		[−1.8 - −1.00]		[−1.73 - −1.40]		[−1.76 - −1.30]	
JAS	1.79	0.09	2.27	0.15	1.68	0.08	2.33	0.16
	[1.61 - 1.98]		[2.06 - 2.59]		[1.53 - 1.86]		[2.11 - 2.68]	
SCAP	1.78	0.09	1.80	0.27	1.73	0.09	2.02	0.22
	[1.61 - 2.00]		[1.14 - 2.13]		[1.57 - 1.92]		[1.56 - 2.36]	
Declare	0.83	0.06	1.05	0.24	0.82	0.05	0.82	0.33
	[0.71 - 0.93]		[0.60 - 1.40]		[0.72 - 0.91]		[0.22 - 1.17]	
Name	0.72	0.06	0.68	0.17	0.76	0.08	1.02	0.21
	[0.60 - 0.84]		[0.39 - 1.06]		[0.61 - 0.91]		[0.66 - 1.29]	
Photo	0.10	0.05	0.31	0.26	0.09	0.05	0.10	0.12
	[0.01 - 0.19]		[−0.06 - 0.87]		[−0.01 - 0.17]		[−0.04 - 0.38]	
Message	0.06	0.07	−0.04	0.50	0.10	0.04	0.08	0.07
	[−0.05 - 0.19]		[−1.00 - 0.53]		[0.03 - 0.17]		[−0.06 - 0.21]	
Brand 1	2.99	0.13	3.02	0.25	3.06	0.11	3.14	0.08
	[2.82 - 3.34]		[2.49 - 3.40]		[2.89 - 3.33]		[2.98 - 3.27]	
Brand 2	1.67	0.11	1.43	0.15	1.98	0.07	1.16	0.22
	[1.49 - 1.88]		[1.21 - 1.71]		[1.83 - 2.12]		[0.89 - 1.63]	
Brand 3	2.44	0.11	2.48	0.37	2.57	0.09	2.62	0.19
	[2.26 - 2.70]		[1.75 - 2.98]		[2.43 - 2.75]		[2.39 - 2.95]	
Brand 4	2.21	0.11	2.41	0.28	2.46	0.10	2.51	0.10
	[2.00 - 2.39]		[1.71 - 2.69]		[2.32 - 2.70]		[2.28 - 2.69]	
Brand 5	1.59	0.10	1.47	0.20	1.60	0.10	1.59	0.14
	[1.40 - 1.81]		[1.15 - 1.76]		[1.41 - 1.78]		[1.38 - 1.80]	
Brand 6	1.67	0.07	1.62	0.38	1.96	0.12	2.10	0.12
	[1.51 - 1.81]		[1.13 - 2.22]		[1.79 - 2.20]		[1.94 - 2.39]	
Brand 7	2.28	0.13	1.29	0.22	1.54	0.11	1.47	0.13
	[2.06 - 2.55]		[0.95 - 1.69]		[1.36 - 1.73]		[1.29 - 1.68]	
Brand 8	2.81	0.12	2.54	0.51	2.25	0.12	2.20	0.17
	[2.57 - 3.00]		[0.95 - 1.69]		[2.08 - 2.50]		[1.88 - 2.46]	
ASC	−0.64	0.13	−0.59	0.09	−0.47	0.08	−0.68	0.13
	[−0.86 - −0.43]		[−0.74 - −0.38]		[−0.61 - −0.33]		[−0.93 - −0.49]	
Lambda			0.64	0.22			0.34	0.09
			[0.17 - 0.97]				[0.16 - 0.51]	
Element of W			$1/d_{ij}$				$1/d_{ij}$	
N of individuals		402		402		737		737
N of observations		3216		3216		5896		5896
Log−Likelihood		−2970.68		−4396.98		−5596.52		−7685.07
BIC		6062.50		8923.17		11323.27		15509.05

Note: S.D. indicates standard deviation of the estimated parameters. The brackets display the minimum and maximum estimated parameters of 95 % credible interval [2.5% - 97.5%].

Table A3
Estimated Mean WTPs (in JPY).

	Kansai sample		Kanto sample	
	Model (A)	Model (B)	Model (A)	Model (B)
JAS	987	1615	1085	1441
	[940 - 1038]	[940 - 1038]	[1038 - 1128]	[1378 - 1519]
SCAP	981	1279	1123	1246
	[941 - 1025]	[1178 - 1362]	[1072 - 1167]	[1212 - 1285]
Declare	415	744	528	502
	[415 - 495]	[573 - 952]	[499 - 559]	[452 - 557]
Name	488	630	400	480
	[393 - 586]	[411 - 796]	[334 - 466]	[278 - 752]
Photo	57	63	58	219
	[−4 - 110]	[−27 - 235]	[3 - 103]	[−45 - 618]
Massage	65	48	31	−29
	[21 - 111]	[−34 - 132]	[−27 - 104]	[−705 - 375]

Note: The estimated WTPs values are calculated using the price parameter and estimated parameters. The brackets display the minimum and maximum estimated parameters of 95% credible interval [2.5% - 97.5%].

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