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ALTERNATIVE APPROACHES TO EVALUATE EXPERTS' PERCEPTIONS: AN APPLICATION TO AGRICULTURE IN BRAZIL[1]

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RESUMO

Os governos intervêm na agricultura por meio de políticas públicas. O objetivo deste trabalho é identificar temas críticos para as políticas públicas em termos de mercado, produção e regulação governamental. Com base em um conjunto de dez principais grupos de riscos agrícolas e as percepções de especialistas relativos tanto à importância destes temas quanto à intensidade das políticas governamentais correspondentes para aliviar os efeitos desses riscos, os temas foram classificados com o uso de métodos multicritério. De modo particular, a discussão concentra-se na lei dos julgamentos de Thurstone e no modelo analítico hierárquico de Saaty. As duas abordagens conduzem a resultados semelhantes. O item "Infraestrutura e logística" foi considerado como o mais importante para ambos os métodos a partir da perspectiva da importância do tema, e é o item menos importante do ponto de vista da intensidade das políticas públicas.

Palavras-chave: Risco, Agricultura, Percepções psicométricas, Modelo de Thurstone, AHP.

ABSTRACT

Governments intervene in agriculture via public policies. It is the objective of this work to identify critical themes for public policies in market, production, and government regulation. Thus, based on a set of ten main groups of agricultural risks and the perceptions of experts relative to both the importance of these themes and the intensity of the corresponding government policies to relieve risk effects, we rank the themes using multicriteria methods. We particularly discuss Thurstone's law of categorical judgments and the Saaty's analytic hierarchy process. The two approaches lead to similar results. Infrastructure and logistics are regarded as the most important item for both methods from the perspective of theme importance, and they are the least important from the perspective of the intensity of public policies.

Keywords: Risk, Agriculture, Psychometric perceptions, Thurstone's law, AHP.

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[1]*Todos os autores assumem a responsabilidade pelo conteúdo do artigo.*

1. Introduction

Agricultural management is subject to uncertainties of several types, for instance institutional government regulations, market uncertainties such as prices, exchange rates and international trade, climate changes, and biological factors.

Farmers face problems associated to logistics, infrastructure and transportation, which increase production costs and reduce the price received by the farmers. Moreover, financial costs resulting from high interest rates also add to production costs. Farmers also experience difficulties associated to imperfections in the institutional and legal regulations affecting the economy as a whole. Besides the market risks, farmers may face production risks. Climate and animal/plant health issues are among the factors outside producer’s control and can generate expressive losses for production.

Uncertainties should be translated into risk probabilities for proper management. It is important to classify themes according to intensity measures, taking into account the numerical probabilities of occurrence in several categories, for example very low (1), low (2), average (3), high (4), and very high (5).

In the operations research literature one notices a plethora of methods developed for the analysis of data resulting from perception evaluations of events or stimuli submitted to the consideration of a judge or a set of judges. Typical examples of these are the AHP – analytic hierarchy process (Saaty, 1990), MACBETH – Measuring Attractiveness by a Categorical Based Evaluation Technique (Bana e Costa and Vansnick, 1994), and Thurstone’s law of comparative and categorical judgments (Torgerson, 1958). See Bana e Costa et al. (2014), Souza and Gomes (2013), Canas et al. (2015), Gazzola et al. (2015, 2016), and Delbari et al. (2016), among others, for typical applications of these approaches.

With the exception of Thurstone’s laws, the methods are deterministic and do not allow for statistical inferences and goodness-of-fit evaluations. Sufficient replication (several judges) is the key concept allowing statistical tests of Thurstone’s approaches. In this context the AHP method can easily be adapted to produce weights comparable to Thurstone’s law of categorical judgments.

Here we follow the AHP and the Thurstone’s law of categorical judgments approaches to analyze the categorical data provided by Gazzola et al. (2015, 2016). In this instance a set of 502 experts were invited to express their views on the importance (scale of 1 to 5) of each of 10 groups of agricultural risks regarding the dimensions of the relevance of each theme and how the government authority is acting to relieve the associated risks.

It is the objective of this work to identify critical themes for public policies in market, production, and government regulation. The risk events associated and their relative importance in the perceptions of experts are analyzed according to popular multicriteria approaches. We intend to show that they lead to similar conclusions, although based on different assumptions regarding the data generating process. The AHP is deterministic and Thurstone’s method is stochastic. Our contribution in this article is twofold. From the applied point of view, we provide a sound basis for government assessment of risk factors of importance to agriculture in Brazil. From a theoretical perspective, we provide an empirical comparison between the AHP and the Thurstone’s law of categorical judgments when enough observations are available to apply the latter. For small samples the AHP is indicated.

To the best of our knowledge no previous work in this respect is available in the literature. We found only one reference (Orbán-Mihálykó et al., 2015), in which the authors used a Thurstone-motivated model for ranking preferences regarding different types of lights. In order to check the rank, they performed the AHP method. The difference to our approach is that here we deal with the Thurstone’s law of categorical judgments instead of the Thurstone’s law of comparative judgments (Thurstone, 1927) to deal with pairwise comparisons (Saaty, 1990), as done by Orbán-Mihálykó et al. (2015). We also found in the literature some uses of the AHP method to assess public policies. In this regard, we mention the studies of Lin et al. (2010), Chanthawong and Dhakal (2016), Petrini et al. (2016), Prochazkova et al. (2015), Requia et al.

(2016) and Schillo et al. (2017). The only use of the Thurstone's law of categorical judgments to evaluate public policies is the proposal of Gazzola et al. (2015), but it is restricted to a linear approximation, which is generalized here.

2. Methodology

2.1 Thurstone's Law of Categorical Judgments

Thurstone's model was developed from psychological assumptions regarding referee behavior when faced with stimuli and a categorical scale. It postulates a psychological continuum, as in Thurstone (1927) and Torgerson (1958). The theory is as follows, as described by Souza (2002). There are *m* (>2) categories and *r* (>1) stimuli. The psychological continuum is the real line. Each time a referee faces a stimulus, a mental discriminal process is put into action and it generates a numerical value on the real line reflecting the stimulus's intensity. The stimuli translate into scale values $\mu_1,\ldots,\mu_r$ on the psychological continuum. Likewise, the categories translate into location values $\tau_1,\ldots,\tau_{m-1}$. The latter quantities form a partition of the real line $(-\infty,\tau_1],(\tau_1,\tau_2],\ldots,(\tau_{m-1},+\infty)$.

As described by Torgerson (1958), the partition relates to stimuli S_i and categories C_j according to the following classification rule. The referee classifies stimulus S_i into $\bigcup_{l=1}^{j} C_l$ if and only if $\mu_i \le \tau_j$. The process inherits randomness from the sampling scheme (replication of referees) and from the fact that, due to stochastic fluctuations, a given stimulus and category do not generate the same scale and boundary values on the psychological continuum when repeatedly evaluated by referees. Randomness leads one to assume that μ_i are means of random variables ξ_i with variance σ_i^2 and that τ_j are means of random variables η_j with variances ϕ_j^2. One assumes row independence and joint normality; that is, ξ_i are uncorrelated and (ξ_i,η_j) are jointly normally distributed. One has primary interest in the means μ_i and the pairwise parametric differences $\mu_i-\mu_j$. These quantities may serve the purpose of assessing stimuli intensities and differences in intensity between two stimuli.

Let π_{ij} denote the probability of locating stimulus S_i in one of the first *j* categories $C_1,C_2,\ldots,C_j$. We assume $\pi_{ij}>0$. We then have (1):

$$
\begin{aligned}
P\left\{S_i \in \bigcup_{l=1}^{j} C_l\right\} &= \pi_{ij} \;\; i=1,\ldots,r \;\; j=1,\ldots,m-1 \\
&= P\left\{\xi_i \le \eta_j\right\} \\
&= P\left\{Z \le \frac{\mu_i-\tau_j}{\sqrt{Var(\xi_i-\eta_j)}}\right\}
\end{aligned}
\tag{1}
$$

Let $g(\cdot)$ denote the probability inverse transformation. The assumption of joint normality leads to the equation (2), relating the cumulative probabilities π_{ij} to the parameters of Thurstone's psychometric model.

$$g(\pi_{ij}) = -\frac{\mu_i - \tau_j}{\sqrt{Var(\xi_i - \eta_j)}} \quad (2)$$

Suppose that enough observations are available to estimate the probabilities π_{ij}. In this context a sample version of the law of categorical judgments is, therefore, shown in (3), where $\hat{\pi}_{ij}$ is the relative cumulative frequency of observations in category C_j.

$$g(\hat{\pi}_{ij}) = -\frac{\mu_i - \tau_j}{\sqrt{Var(\xi_i - \eta_j)}} + u_{ij} \quad (3)$$

The vectors $u_i' = (u_{i1}, u_{i2}, \ldots, u_{im-1})$ are independently distributed with a distinct variance matrix for each *i*. Clearly, we have (4), where $\hat{p}_{il}$ represents the proportion of times that the referees classify stimulus S_i into C_l.

$$\hat{\pi}_{ij} = \hat{p}_{i1} + \hat{p}_{i2} + \ldots + \hat{p}_{ij} \quad (4)$$

At this level of generality, the sample model is not identifiable and further restrictions are imposed on the parameters to identify the model. Three alternatives are considered, leading to the models below, labeled by Torgerson (1958) as Models B, C, and D.

<u>Model D</u>:

Model D assumes $Var(\xi_i - \eta_j) = 1$ for any (i, j). Identifiability is obtained by imposing additionally $\sum_{i=1}^{r} \mu_i = 0.$

<u>Model B</u>:

Model B assumes $Var(\xi_i - \eta_j) = \delta_i^2 > 0$; that is, the model is heteroskedastic in stimuli (rows). Identifiability is obtained by imposing two additional conditions: $\sum_{i=1}^{r} \frac{1}{\delta_i} = r$ and $\sum_{i=1}^{r} \frac{\mu_i}{\delta_i} = 0.$

<u>Model C</u>:

Model C assumes $Var(\xi_i - \eta_j) = \theta_j^2 > 0$; that is, the model is heteroskedastic in categories (columns). Identifiability is obtained by imposing $\sum_{j=1}^{m-1} \frac{1}{\theta_j} = m - 1$ and $\sum_{j=1}^{m-1} \frac{\tau_j}{\theta_j} = 0.$

Models B, C, and D may be estimated by generalized least squares or maximum likelihood. For the latter the likelihood function is given by (5), where m_i is a fixed row total, y_{ij} is the frequency in cell (i, j), and $\sum_{j=1}^{m} p_{ij} = 1.$

$$\sum_{i=1}^{r} \ln\left(\frac{m_i!}{y_{i1}!\ldots y_{im}!}\right) + \sum_{i=1}^{r}\sum_{j=1}^{m} y_{ij} \ln\left(p_{ij}\right) \tag{5}$$

Here, for Model B we have (6):

$$p_{i1} = g^{-1}\left(\frac{\tau_1 - \mu_i}{\delta_i}\right), \;\; p_{ij} = g^{-1}\left(\frac{\tau_j - \mu_i}{\delta_i}\right) - g^{-1}\left(\frac{\tau_{j-1} - \mu_i}{\delta_i}\right) \; j = 2,\ldots,m-1 \tag{6}$$

For Model C we have (7):

$$p_{i1} = g^{-1}\left(\frac{\tau_1 - \mu_i}{\theta_1}\right), \;\; p_{ij} = g^{-1}\left(\frac{\tau_j - \mu_i}{\theta_j}\right) - g^{-1}\left(\frac{\tau_{j-1} - \mu_i}{\theta_{j-1}}\right) \; j = 2,\ldots,m-1 \tag{7}$$

For Model D we have (8):

$$p_{i1} = g^{-1}\left(\tau_1 - \mu_i\right), \;\; p_{ij} = g^{-1}\left(\tau_j - \mu_i\right) - g^{-1}\left(\tau_{j-1} - \mu_i\right) \; j = 2,\ldots,m-1 \tag{8}$$

All that is needed for inferences regarding the stimuli are the estimates of μ_i. Any monotonic transformation of these quantities will lead to the same ranking of the stimuli and the same pairwise comparisons. Souza (2002) suggests the ratio (9) as a measure of relative intensity for stimulus *i*. This definition relies on the assumption of a lognormal distribution on the psychological continuum and can be easily derived for Model D. This approach makes the results comparable to the AHP's outcomes. The other models lead to odds ratios dependent on nuisance parameters.

$$w_i = \frac{\exp(\mu_i)}{\sum_{\nu=1}^{r} \exp(\mu_\nu)} \tag{9}$$

2.2 Analytic Hierarchy Process

As an alternative to the hierarchy induced by the law of categorical judgments, one may use the analytic hierarchy process (AHP). See Saaty (1990). The idea follows.

Let $\left(S_1, S_2, ..., S_r\right)$ be the sequence of stimuli for which one wants to assign the sequence of weights $\left(w_1, w_2, ..., w_r\right)$ reflecting stimuli intensities. A judge manifests his perception on the relative importance of stimulus S_i relative to stimulus S_γ on a given numerical scale using the positive constant $a_{i\gamma}$. Let $A = (a_{i\gamma})$ be the evaluation matrix of order *r*. We assume:

1. If $a_{i\gamma} = \alpha$, then $a_{\gamma i} = \alpha^{-1}$.
2. If S_i and S_γ are equally important, then $a_{\gamma i} = a_{i\gamma} = 1$.

Therefore, $A = (a_{i\gamma})$ is a reciprocal matrix (10).

$$A = \begin{bmatrix} 1 & a_{12} & \dots & a_{1r} \\ 1/a_{12} & 1 & \dots & a_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ 1/a_{1r} & 1/a_{2r} & \dots & 1 \end{bmatrix} \qquad (10)$$

As shown by Saaty (1990), the problem of the determination of weights is solved by looking for the eigenvector x (sum normalized) corresponding to the maximum eigenvalue. Assume that $a_{i\gamma} = p_i / p_\gamma$, where p_ν are positive numbers reflecting the perception of importance of the stimulus S_ν in the judge's concept. In this instance the largest eigenvalue of $A = (a_{i\gamma})$ is r and the corresponding eigenvector is the first column sum normalized.

The importance scale suggested by Saaty (1990) for pairwise evaluation (p_ν's) is: 1 – equal importance, 3 – moderate importance, 5 – strong importance, 7 – very strong importance, and 9 – extreme importance. We notice that this scale can be obtained from the scale 1, 2, 3, 4, and 5 through the transformation $2p-1$.

The perception of several experts can be pooled into a reciprocal evaluation matrix using the geometric average of the individual perceptions.

3. Data

The application carried out here is derived from the study by Gazzola et al. (2015). As a result of a 2014 workshop, which took place at the headquarters of the Brazilian Agricultural Research Corporation (Embrapa), 10 critical areas were very important for public policies regarding the Brazilian agricultural sector: 1. extreme weather events and fire; 2. animal health; 3. plant health; 4. production management; 5. natural resources management; 6. market/commercialization; 7. credit; 8. international trade; 9. regulatory framework and interest conflict; and 10. infrastructure and logistics.

These areas were evaluated by 502 experts on the scale 1–5, where 1 represents the least intense perception of importance and 5 the most intense. The experts were asked 2 questions: the importance of the area and the intensity of public (government) policies handling each subject. Tables 1 and 2 show the response frequencies in each case. For example, in Table 1 six experts classified the item "Extreme weather events and fire" as of the least importance. Similar interpretation applies to Table 2.

Table 1. Frequencies of responses: area importance.

Categories/importance	**1**	**2**	**3**	**4**	**5**
Extreme weather events and fire	6	26	70	169	162
Animal health	3	15	39	160	204
Plant health	2	15	33	178	198
Production management	4	31	104	165	124
Natural resources management	6	21	69	158	173
Market/commercialization	8	21	93	182	118
Credit	2	22	86	185	127
International trade	6	21	96	172	119
Regulatory framework and interest conflict	7	22	116	140	123
Infrastructure and logistics	7	8	22	81	306

Source: Gazzola et al., 2015.

Table 2. Frequencies of responses: intensity of public policies.

Categories/importance	1	2	3	4	5
Extreme weather events and fire	93	179	107	41	12
Animal health	24	93	164	111	11
Plant health	37	114	164	88	13
Production management	75	174	128	36	5
Natural resources management	73	150	147	48	9
Market/commercialization	46	136	165	56	7
Credit	13	70	166	137	24
International trade	38	112	159	75	8
Regulatory framework and interest conflict	57	155	137	35	5
Infrastructure and logistics	160	155	62	24	18

Source: Gazzola et al., 2015.

4. Estimation Results

We estimated Thurstone's Models B, C, and D by maximum likelihood. The parameters were first estimated by generalized least squares (Souza, 2002), and the resulting estimates were used as initial values in the maximum likelihood routine. We used PROC NLMIXED (SAS Institute Inc., 2015) to fit the models. Table 3 shows the goodness-of-fit statistics for Models B, C, and D.

Table 3. Goodness-of-fit statistics for maximum likelihood and generalized least squares. AIC is the Akaike Information Criterion, BIC is the Bayesian Information Criterion, MSE is the Mean Square Error and R2 is the square of the correlation between observed and predicted values.

Perspective	Model	-2 log likelihood	AIC	BIC	MSE	R2
Area importance	B	10,088	11,144	10,139	1.568	0.982
	C	10,090	10,122	10,126	1.349	0.982
	D	10,138	10,164	10,168	1.947	0.957
Intensity of public policies	B	11,010	11,054	11,061	3.330	0.952
	C	11,005	11,037	11,042	2.449	0.971
	D	11,083	11,109	11,113	2.762	0.950

Source: Prepared by the authors.

We see from Table 3 that all the models are approximately equivalent regarding the fit. Model C is slightly better for both perspectives. Table 4 shows the parameter estimates for Model C and Table 5 the weights indicating the relative importance of each area, computed with the parameters estimates of $(\mu_1, \ldots, \mu_{10})$ in Table 4.

For the area importance, based on the weights shown in Table 5, the stimuli rank order is 10 (infrastructure and logistics), 2 (animal health), 3 (plant health), 5 (natural resources management), 1 (extreme weather events and fire), 7 (credit), 6 (market/commercialization), 8 (international trade), 4 (production management), and 9 (regulatory framework and interest conflict). The pairwise nonsignificant effects are 1 and 5, 2 and 3, 4 and 6, 4 and 7, 4 and 8, 4 and 9, 6 and 7, 6 and 8, 6 and 9, 7 and 8, 7 and 9, and 8 and 9. Any other comparison is statistically significant (p-value <= 0.05).

For the intensity of public policies the rank order is 7, 2, 3, 8, 6, 5, 9, 4, 1, and 10 (see table 5). The pairwise nonsignificant effects are 1 and 4, 3 and 8, 4 and 5, 4 and 9, 5 and 9, and 6 and 8. Any other pairwise comparison is statistically significant (p-value <= 0.05).

The AHP estimation is derived from Tables 1 and 2 considering the scale transformation to 1, 3, 5, 7, 9. We illustrate the computations for Table 1. Firstly, one computes the vector of geometric means: (6.738 7.334 7.372 6.407 6.851 6.443 6.683 6.481 6.340 7.859). Notice that in this context, for example: $6.738 = \exp((6\ln(1) + 26\ln(3) + 70\ln(5) + 169\ln(7) + 162\ln(9))/433)$.

The final weights are obtained from the vector above, normalizing by this quantity and adjusting for unit sum.

Table 4. Parameter estimation for Thurstone's Model C.

Parameter	Area importance		Intensity of public policies	
	Estimate	Standard error	Estimate	Standard error
μ_1	1.0589	0.03840	-0.6930	0.04265
μ_2	1.2426	0.04419	-0.05403	0.04630
μ_3	1.2355	0.04464	-0.2172	0.04370
μ_4	0.8977	0.04159	-0.6253	0.04320
μ_5	1.0955	0.03859	-0.5304	0.04201
μ_6	0.9218	0.04116	-0.3791	0.04258
μ_7	0.9560	0.03904	0.1544	0.05249
μ_8	0.9191	0.04104	-0.2618	0.04403
μ_9	0.8844	0.04367	-0.5427	0.04401
μ_{10}	1.5727	0.06967	-1.0134	0.04872
τ_1	-2.1397	0.2705	-1.6831	0.04069
τ_2	-0.8494	0.1137	-0.6475	0.03225
τ_3	0.8973	0.1391	0.4996	0.02838
τ_4	2.09180	0.19126	1.8310	0.0564
θ_1^{-1}	0.1108	0.2462	1.3234	0.07531
θ_2^{-1}	0.6693	0.1046	1.3747	0.06217
θ_3^{-1}	1.5450	0.1265	1.0591	0.05333
θ_4^{-1}	1.67485	0.1786	0.2429	0.1061

Source: Prepared by the authors.

Table 5. Weights for Thurstone's Model C.

Weight	Area importance		Intensity of public policies	
	Estimate	Standard error	Estimate	Standard error
w_1	0.09580	0.003169	0.07205	0.002942
w_2	0.1151	0.003892	0.1365	0.005528
w_3	0.1143	0.003918	0.1159	0.004556
w_4	0.08154	0.003288	0.07709	0.003166
w_5	0.09937	0.003198	0.08477	0.003363
w_6	0.08353	0.003260	0.09862	0.003859
w_7	0.08643	0.003053	0.1681	0.007519
w_8	0.08330	0.003238	0.1109	0.004416
w_9	0.08046	0.003459	0.08373	0.003456
w_{10}	0.1601	0.009147	0.05229	0.002497

Source: Prepared by the authors.

Table 6 shows the results of the AHP solution for both perspectives under analysis. It is impossible to separate the weight effects statistically with the AHP method. For the area importance, we identify the group of stimuli 10, 3, and 2 as the most intense (higher weights), followed by the group 5, 1, 7 and the group 8, 6, 4, 9. For the intensity of public policies, stimulus 7 is the most intense, followed by 2, the group 3, 8, stimulus 6, the group 9, 5, 4, stimulus 1, and stimulus 10.

Table 6. AHP weights.

Weights	Area importance	Intensity of public policies
w_1	0.098347	0.082163
w_2	0.107047	0.123171
w_3	0.107607	0.112730
w_4	0.093523	0.085899
w_5	0.099998	0.091304
w_6	0.094046	0.101958
w_7	0.097552	0.137989
w_8	0.094609	0.109179
w_9	0.092549	0.091564
w_{10}	0.114722	0.064043

Source: Prepared by the authors.

More informative statistically regarding the two methods (Thurstone's Model C and the AHP) and the two perspectives (area importance and intensity of public policies) is Table 7, showing the pairwise rank correlations between all the derived classifications. We see from Table 7 that the rank correlations between perspectives for both methods are low and do not differ significantly from zero. The conclusion is that experts perceive government policies as not aligned with their perceptions about the real importance of the subjects. Infrastructure and logistics, for example, are regarded as the most important item for both methods from the perspective of area importance and the least important from the perspective of the intensity of public policies. Although it is hard to separate effects with the AHP method, the ranks are highly correlated with Thurstone's classification from both perspectives. The lowest correlation is 97.6%. We emphasize the impossibility of statistically comparing the data generating processes regarding AHP and Thurstone approaches. However, the similarities in the final classifications are remarkable.

Table 7. Spearman rank correlations. The figures in parentheses are p-values.

Method/perspective	Thurstone/area importance	Thurstone/public policies	AHP/area importance	AHP/public Policies
Thurstone/area importance	1	0.05455 (0.8810)	0.97576 (<0.0001)	-0.01818 (0.9602)
Thurstone/public policies		1	0.05455 (0.8810)	0.98788 (<0.0001)
AHP/area importance			1	-0.01818 (0.9602)
AHP/public policies				1

Source: Prepared by the authors.

5. Summary and Conclusions

Based on a survey, in which 502 experts on Brazilian agriculture were asked to convey their perceptions in regard to the area importance and intensity of public policies of major items that are essential for agricultural sustainability, we applied Thurstone's law of categorical judgments and Saaty's AHP method to rank the perceptions and measure the consistency between the two perspectives. To obtain comparable results, the AHP approach was adapted to bring the data to the AHP typical scale, to ease the computations, and to make the results comparable to Thurstone's.

AHP weights are easy to compute but lead to difficulties in interpretation, since one cannot properly separate weight perceptions, which are also scale dependent. The model cannot be tested either. Thurstone's fit may be tested statistically using deviance analyses. In our application the three Thurstone's models were not rejected using a chi-square test for both perspectives. The scale deviances for Model C are 1.8394 and 1.9524 for the area importance and the intensity of public policies, respectively. Both are not statistically significant.

We concluded that the ranks induced by both approaches are highly correlated and indicate very poor association between the area importance and the intensity of public policies. For the AHP model this correlation is negative. The Model C classification of items from the perspective of area importance is 10 (infrastructure and logistics), 2 (animal health), 3 (plant health), 5 (natural resources management), 1 (extreme weather events and fire), 7 (credit), 6 (market/commercialization), 8 (international trade), 4 (production management), and 9 (regulatory framework and interest conflict). Item 10 is by far the most important perception. Item 7 is the most intense for public policies. Credit is of no help if logistics and infrastructure problems are not solved. For Thurstone's models, with the exception of an inversion between item 6 and item 8 in the area importance, the ranks are the same for both perspectives.

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