From thresholds to risk factors: Prioritization of socio-economic risks to sustainable tourism development

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Abstract

This paper contributes to the ongoing efforts for assessing tourism sustainability by focusing on the analysis and interpretation of the perceptions of local residents in relation to the thresholds of social carrying capacity. More specifically, we propose a statistical framework that supports identification of risk factors contributing to negative perceptions of tourism, rather than focusing on identification of a clear threshold for a given sustainability indicator. This framework is based on explanatory and predictive modeling and adopts multiple regression analysis, dominance analysis and random forest method to identify the risk factors and their relative importance. Estimating the relative importance of each risk factor provides a means to prioritize management and monitoring of sustainability indicators. The proposed statistical framework is intuitive and its usefullness is demonstrated on the case of the city of Split, one of the major tourism destinations in Croatia. The findings demonstrate that apartmentization, and perceived changes in city appearance and its authenticity are the key risk factors that affect overall perception of tourism development in Split.

Key words: tourism sustainability; risk factor modeling; relative importance; dominance analysis; predictive modelling; random forest

1. Introduction

Although the findings are mixed, tourism is typically considered a means to stimulate economic growth, especially in developing countries, but with the significant socio-cultural and environmental costs (Camatti et al., 2020; Garcia et al., 2015; Gossling et al., 2020; Kim et al., 2013; Mihalic, 2020; Uysal et al., 2016; Woo et al., 2022). Measuring socio-economic change driven by tourism development is closely linked to the concept of overtourism, which has become one of the focal points of tourism research in the last decade. Overtourism refers to the pressures of the number, density and types of tourists on local communities, when the impacts of tourism exceed thresholds of physical, ecological, social, economic, psychological, and/or political capacity (TRAN, 2018). A large body of research was dedicated to assessing tourism carrying capacity of a destination, i.e., to finding a threshold such as the maximum number of visitors per day that could be considered acceptable from the perspective of tourism sustainability, especially considering negative impacts of tourism on environmental and social context (UNWTO, 2023). Its sub-concept of social carrying capacity refers to the number of visitors at which the negative social impacts of tourism outweigh the positive impacts, leading to negative perceptions of tourism within a host community. However, there is no standardized methodological approach or well-defined measures for assessing the social carrying capacity of tourism (UNWTO, 2023).

TRAN report (2018) suggests that an effective early warning tool for overtourism cannot be established „because of the complex multifaceted causes for overtourism, and an overall lack of reliable and well-defined indicators with clear thresholds.“ Relevant economic, environmental and social thresholds of tourism development are known to vary by location and over time (UNWTO, 2023), since they depend on the subjective factors arising from the perception of individuals. For example, crowding, as one of the most obvious tourism impacts, is considered a psychological construct strongly influenced by personal characteristics rather than an objective measure of the density of visitors (Neuts et al., 2012).

Due to the subjective nature of thresholds of sustainability indicators, standardizing the thresholds by identifying the threshold (e.g., 60% of residents with a negative perception of spatial impacts of tourism) above which the impact of a given indicator could be considered unacceptable is a pointless task. Normative research on determining the maximum acceptable threshold of visitor intensity has been typically focused on visual methods – survey questionnaires with realistic images of the landscape or other area of interest and systematic manipulation of the number of people in the images. Based on the respondent's perception of the acceptability or desirability of each image, the highest acceptable or desirable level of use is estimated to determine visitation norms. This approach, in addition to focusing exclusively on crowding management, has some other disadvantages such as inappropriateness for the telephione interview as the method of data collection, risk of bias caused by the order of questions, limited spatial coverage (i.e., applicable to micro-locations only) and ignorance of environmental factors that may influence crowding perceptions, such as noise and heat/temperature (Klanjšček et al., 2018).

A potentially more useful approach to measure carrying capacity in the context of tourism is to determine which key indicators to monitor and then define the acceptable level of change in these key indicators. This approach is promoted by the Limits of Acceptable Change and Visitor Impact Management methods (Ahn et al., 2002), but is dependent in political decisions. UNWTO (2023) suggests that the framing of thresholds can be considered from a perspective of risk, which is exactly the approach we have taken in this paper. This alternative approach is based on prioritization framework that identifies the risk factors and their relative importance to support more efficient management and monitoring of tourism impacts. Identification of risk factors and their relative importance is based on statistical criteria (i.e., statistical significance, goodness-of-fit measures and predictive accuracy) and includes both explanatory and predictive modeling to derive valid inferences about the sustainability indicators.

2. Methodological approach

2.1. Risk factor modeling

Perceptions of host communities are typically measured by conducting resident surveys; however, methods applied lack harmonization and comparability (UNWTO, 2023). While people's perceptions are not necessarily aligned with objective measures, the perceptions commonly drive tourism decisions and are therefore a key measure when assessing the social impacts of tourism (UNWTO, 2023). Resident surveys need to address various impacts of tourism on local community – environmental, physical, economic, social and psychological (TTRA, 2018). This multidimensionality of tourism impacts makes indetification of risk factors particularly challenging. In this paper, we propose the following statistical criteria for identification and prioritization of risk factors – statistical significance (as a threshold value for determining relevant risk factors amongst various tourism impacts) and contribution of each risk factor to the goodness of fit of a model, in terms of changes in the R^2.

To determine the risk factors, we regress the perceptions of specific tourism impacts on the overall perception of tourism in the destination and define the risk factors as those that significantly affect the dependent variable, i.e., explain significant amount of variablity in the overall perception of tourism while holding other variables in the model fixed. The dependent variable has been operationalized as a binary variable taking a value of 1 if the overall impact of tourism is perceived as positive, and the value of 0 if perceived as neutral or negative. A multiple binary logistic regression model was used to estimate the impact of a given predictor on the overall perception of tourism while accounting for the impacts of all other predictors and controlling for background variables (e.g., gender, age, level of education and receiving or not income from tourism). A comprehensive set of relevant independent variables that will consider multifaceted impacts of tourism in a particular destination should be included in the model, so to avoid omitted variable bias and invalid inferences.

The purpose of multiple regression is to explain outcome variable from several well-selected predictors, while controling for confounding and other types of biases (Azen & Budescu, 2003). The full model simultaneously includes all independent variables/covariates with theoretical background, regardless of their statistical significance, in order to control for confounding (Bursac et al., 2008). However, when selecting a 'true' model a set of initial predictors is reduced to a subset that most adequately describes the variation in outcome variable. A parsimonious model is usually desirable since it enhances numerical stability (of the parameter estimates) and generalizability (of the results), while reducing multicollinearity (Bursac et al., 2008; Shmueli, 2010). The selection of variables that should be kept in the model could be governed by various criteria, such as statistical significance and information criteria (e.g., AIC). Automated variable selection methods that use statistical significance to decide which variables to retain in the model are considered inappropriate in explanatory modeling since this approach entirely neglects the theoretical model (Shmueli, 2010). These methods optimize overall model fit without considering the roles of individual variables. Thus, variable selection should be performed in a statistically more flexible manner. We have adopted the purposeful variable selection approach suggested by Bursac et al. (2008) and Hosmer and Lemeshow (2000), which has the ability to retain not only significant covariates but also important confounding variables in the logistic regression model, and this is particularly relevant for risk factor modeling.

2.2. Estimating relative importance

The relative importance of examined exploratory variables was determined by performing (a) dominance analysis and (b) variable importance assessment in random forest models. In this way, we are able to evaluate variable importance in terms of both, explained variability and predictive power.

2.2.1. Dominance analysis

Dominance analysis is a popular method to determine the relative importance of correlated variables. It ranks a given predictor by measuring how much it contributes to explaining the overall perception of tourism, measured as change in McFadden's R^2, in all possible subset models formed by the combinations of other predictors. Thus, when evaluating variable importance in terms of additional explained variability, dominance analysis considers the relationships between the independent variables in the model. Not taking into account those relationships may bias the estimates, in particular when variables are highly correlated (Rossi et al., 2020) which is typically the case in the resident surveys. When using a set of correlated predictors, the measures of relative importance are affected by other predictors in the model (those controlled for) and by other predictors not included in the model (Azen & Budescu, 2003).

Dominance analysis is a partitioning method that measures the percentage of variation explained by each predictor in relation to all possible combinations of all other predictors. Therefore, the measure of variable importance reflects its univariate effect (when all other predictors are removed from the model), its partial effect (conditional on subsets of predictors) and its total effect (conditional on all other predictors) (Budescu, 1993). Dominance is examined for all pairs of predictors. In the most strict sense, i.e. that of complete dominance, one variable dominates the other if it is more useful in all subset regressions (Budescu, 1993). Qualitative analysis of dominance examines the usefullness of the predictors across all subset regressions, for all pairs of predictors. If complete dominance between variables is achieved, quantitative analysis provides a summary of usefullness measures/dominance statistics for a given predictor by averaging them across all subset models that include that predictor (Budescu, 1993). Since complete dominance often cannot be established, studies often rely on the less restrictive type of dominance, i.e., general dominance, which calculates the average conditional contribution over all model sizes for each predictor and ranks all predictors based on their average contribution (Azen & Traxel, 2009).

2.2.2. Predictive modelling

A common misunderstanding in the process of statistical modeling is that models with high explanatory power also have high predictive power (Shmueli, 2010). The objective of explanatory modeling is to find the 'true' model, i.e., to most accurately represent underlying theory by minimizing the bias arising from model misspecification. On the other hand, predictive modeling tends to trade off bias for descreased estimation variance (i.e., improved precision), to obtain better predictions even if the statistical model is theoretically wrong. Nevertheless, predictive modeling can capture complex patterns and relationships between the variables, and thus suggest potential improvements to explanatory models (Shmueli, 2010).

The variable importance assessed by random forest models was evaluated as a mean decrease in accuracy and thus enables assessment of the variable importance in terms of predictive power. Random forest models are built by applying a conditional random forest framework which results with unbiased forests in terms of variable selection, while feature importance is assessed by following the conditional permutation scheme which relies on the permutation principle of the mean decrease in accuracy importance (Strobl et al., 2008). This approach guarantees unbiased variable selection and variable importance for predistors of different types and takes into accound the correlations between predictors. The random forest analysis was performed in the R package 'party'.

3. Study setting

Measuring tourism impacts is of the greatest relevance at the local scale at which the perceptions and attitudes towards tourism are formed (UNWTO, 2023). Measuring the impacts at the level of local tourism destinations is most useful for decision making. The methodological framework presented in this paper has been applied to evaluate residents' perceptions of tourism impacts in the city of Split. Split is the 2nd largest city in Croatia and the largest Croatian city on the Adriatic Coast. It is populated by approximately 160,000 inhabitants (CBS, 2022). The Historical Complex of Split, inscribed on the World Heritage List in 1979, includes the ruins of Diocletian's Palace built between 295 to 305 as well as a number of Medieval buildings. The city attracts a huge number of tourists, with 2,620,705 number of bed-nights realized in commercial accommodation establishments in 2022. The pressure of intense tourism growth during the last decade led to the changes in local community driven by displacement of local population from the city center where living premises were tranformed to short-term tourism rentals, as well as to an increase in real estate prices and changes in place character (Matečić et al., 2022). The tourism activity is heavily concentrated in the historical city centre and influenced by seasonality.

The survey of local residents was conducted in June 2022 on a sample of 385 respondents/ permanent residents of Split. Computer Assisted Telephone Interview (CATI) was used as a data collection method. The data were collected by the professional market research company IPSOS. A structured questionnaire was used as a survey instrument, and included the data on socio-demographic characteristics, perceptions of tourism impacts and preferences for further tourism development. The sample is representative at the city level by gender and age group of residents.

4. Results

4.1. Exploratory data analysis

The majority of respondents were females (54%). Every second respondent was younger than 50 years of age, and 40% had university or higher education. For every tenth respondent tourism was a major source of income, for 29% partial source of income, while 61% did not receive any income from tourism.

Descriptive analysis of residents' perceptions is shown in Table 1. Since not all variables are measured on the prevalent 5-point Likert-type scale, percentages are used instead of means or medians as a summary measure. The most negative perceptions of tourism impacts are associated with increase in the prices – residents dominantly believe that tourism development strongly influenced the increase in the prices of real estate (90%), long-term rental accommodation (88%) and restaurant/cafes (84%). Furthermore, 85% perceives parking problems during a tourist season as a serious everyday-life hassle, while 71% sees waste disposal as a serious problem. The majority of residents (58%) perceive apartmentization as a factor that negatively affects life in the city and every second resident thinks that Split looses its character, its authenticity. The question on the displacement of locals from the historic city center to suburbs, which in contrast to other questions reflects actual behavior and not the perceptions, reveals that 29% of residents have either moved from the city center or their family/friends have done so. The variable that recorded the lowest prevalence of negative tourism impacts is city appearance – every fourth resident thinks that tourism development negatively affected the aesthetics of the city.

Table 1. Summary of resident perceptions of tourism impacts

Code	Variable	%	Rank*
overall	**Positive perception of overall tourism impacts**	52.52	-
Serious crowding-related problems:			
noise	Noise	33.83	16
traffic	Traffic jams	70.03	7
crowds	Crowded streets/public places	37.69	15
transport	Crowding in public transport	33.53	18
waste	Improperly disposed waste	71.22	6
smell	Unpleasant smells (from containers and waste bins)	55.19	10
behavior	Inappropriate tourist behavior	47.48	12
parking	Parking problems (no spaces available)	84.87	3
Increased prices:			
realestate	Real estate	90.21	1
rent	Rental prices/ Rental accommodation	88.43	2
utilities	Utilities (electricity, water, gas)	43.92	14
groceries	Food and beverages in stores	64.09	8
restaurants	Prices in restaurants/cafes	83.68	5
Other specific negative impacts of tourism:			
appearance	City appearance (unattractive, unpleasant)	25.52	20
apartmentization	Apartmentization	58.46	9
authenticity	Authenticity/place identity loss	49.55	11
displacement	Displacement of locals	29.38	19
space	Inadequate usage of public space	33.83	17
services	Reduced availability of public services	46.88	13
housing	Lack of affordable housing opportunities	84.47	4

* Rank of specific tourism impacts according to the prevalence of negative perceptions.

Before conducting the multiple regression analysis, the explanatory factor analysis was performed to avoid multicollinearity among the predictors. Multicollinearity or high correlations between two or more predictors is a serious issue that affects parameter estimation (Garver & Williams, 2019). This is an important problem in explanatory modeling because statistical significance of explanatory variables and their individual contributions to a dependent variable are usually of research interest (Shmueli, 2010).The problem of multicollinearity often occurs in tourism research, and manifests itself in unstable and biased parameter estimates (Assaf et al., 2019). The studies of the attitudes of the local population typically include a number of interrelated variables, of which some may be considered integral parts of the same multidimensional construct.

An exploratory factor analysis was applied on a set of crowding-related tourism impact items (Table 2). Due to the ordinal nature of data, polychoric correlations among variables were used as the input for factor analysis. The Kaiser's measure of sampling adequacy (0.702) was considered acceptable, indicating appropriateness of performing the factor analysis. Kaiser's criterion and scree plot based on initial eigenvalues of principal components suggested that two factors should be retained, explaining 57% of the variance in the original data. Orthogonal (varimax) rotation was applied to derive the two factors. According to the factor loadings in Table 2, the extracted factors were interpreted as 'social crowding' (Factor 1) and 'waste and cleanliness' (Factor 2).

Table 2. Results of exploratory factor analysis on a set of crowding-related items

Item	**Factor1: Social crowding**	**Factor2: Waste and cleanliness**	Communality estimates
noise	**0.504**	0.293	0.340
traffic	**0.816**	0.108	0.677
crowds	**0.598**	0.192	0.395
transport	**0.549**	0.148	0.324
waste	0.071	**0.802**	0.648
smell	0.226	**0.665**	0.494
behavior	0.224	**0.571**	0.376
parking	**0.545**	0.109	0.309
Variance Explained	1.983	1.579	

An exploratory factor analysis was also applied on a set of tourism impact items associated with an increase in prices (Table 3). The Kaiser's measure of sampling adequacy (0.714) was considered acceptable, indicating appropriateness of performing the factor analysis. Kaiser's criterion and scree plot based on initial eigenvalues of principal components suggested that two factors should be retained, explaining 62% of the variance in the original data. Orthogonal (varimax) rotation was applied to derive the two factors. According to the factor loadings in Table 3, the extracted factors were interpreted as 'current expenses' (Factor 3) and 'housing affordability' (Factor 4).

Table 3. Results of exploratory factor analysis on a set of items measuring tourism impact on prices

Item	**Factor3: Current expenses**	**Factor4: Housing affordability**	Communality estimates
housing	-0.077	**0.669**	0.453
realestate	0.197	**0.780**	0.646
rent	0.239	**0.736**	0.599
utilities	**0.857**	0.056	0.737
groceries	**0.881**	0.089	0.785
restaurants	**0.547**	0.469	0.519
Variance Explained	1.911	1.827	

4.2. Risk factor modeling

A risk factor modeling was performed by using a binary logistic regression analysis and modeling the probability of non-positive perception of overall tourism impacts. Several models were estimated, starting with the simple regression models which included a single independent variable. In a simple regression all variables had statistically significant effect on the overall perception of tourism impacts besides 'Factor3: Current expenses' (p = 0.340). Interestingly, this variable became significant in the multiple regression model that accounted for relationships between independent variables. In the full model, which includes all variables of interest, three of them were not statistically significant: 'Factor2: Waste and cleanliness' (p = 0.416), 'displacement' (p = 0.392) and 'space' (p = 0.543), while 'Factor4: Housing affordability' was marginally significant. The parsimonious selection model was estimated next and excluded potentially irrelevant variables (Factor2, displacement and space). When control variables were added to this model, the effect of 'Factor3: Current expenses' was insignificant. Among the control variables, age group and education level explained significant amount of variation in the overall perception of tourism impacts, while gender and receiving income from tourism were not significant controls. A stepwise regression models based on statistical significance criteria (with a p-value cut-off value of 0.25 instead of a typical 0.05 to avoid failing to detect some important variables), purposeful selection criteria (Bursac et al., 2008) and information minimization criteria (Akaike Information Criteria, AIC) were estimated and yielded consistent results. Standardized regression coefficients indicated that 'appearance' and 'apartmentization' were the most influential variables followed by 'authenticity'. However, using standardized regression coefficients to infer relative importance of variables in regression analysis is not appropriate. Standardized regression coefficients are directly related to the additional contribution of each predictor in the presence of other predictors, thus they are very sensitive to correlations among predictors and only consider a limited information in comparison to dominance analysis which estimates contributions to all subset models (Azen & Traxel, 2009).

Table 4. Identification of risk factors – results of logistic regression analyses (some variables were reverse-coded)

Variable	Simple regression models		Multiple regression models					
			Full model		Purposeful selection model		Selection model with controls	
	Std. Est.	p-value	Std. Est.	p-value	Std. Est.	p-value	Std. Est.	p-value
Factor1: Social crowding	-0.268	< 0.001	-0.257	0.005	-0.268	0.002	-0.286	0.002
Factor2: Waste and cleanliness	-0.194	0.002	-0.072	0.416	-	-	-	-
Appearance	-0.581	< 0.001	-0.439	<.0001	-0.458	<.0001	-0.458	<.0001
Apartmentization	-0.628	< 0.001	-0.444	<.0001	-0.476	<.0001	-0.490	<.0001
Authenticity	0.399	< 0.001	0.327	0.000	0.343	<.0001	0.289	0.001
Displacement	0.189	0.002	0.068	0.392	-	-	-	-
Space	-0.432	< 0.001	-0.057	0.543	-	-	-	-
Services	-0.343	< 0.001	-0.201	0.020	-0.212	0.012	-0.190	0.028
Factor3: Current expenses	-0.058	0.340	-0.207	0.019	-0.185	0.029	-	-
Factor4: Housing affordability	0.321	< 0.001	0.145	0.101	0.149	0.090	0.204	0.027

Age1	-	-	-	-	-	-	-0.219	0.009
Age2	-	-	-	-	-	-	-0.278	0.002
Edu1	-	-	-	-	-	-	-0.196	0.028
Edu2	-	-	-	-	-	-	-0.156	0.074
N	337		337		337		337	
Max-rescaled R^2	-		0.508		0.503		0.532	
AIC	-		326.98		322.87		316.86	

Std. Est. = Standardized Estimate
AIC = Akaike Information Criterion

4.3. Dominance analysis

Relative importance of variables was estimated by using dominance analysis (Table 5). All variables that were candidates for multiple regression model were considered, since all were statistically significant in at least one regression model. Dominance analysis was performed on two models – Model I without control variables and Model II which included control variables when estimating the relative importance of predictors. Two measures of dominance were used – complete dominance and general dominance. In Model I, full ordering of variables could not be achieved when using more restrictive, complete dominance criterion. However, 'apartmentization' and 'appearance' dominated all other variables, and 'authenticity' dominated all but the two most important variables. These were also the three most important variables according to their average contribution based on the general dominance criterion. Among the other variables, 'space' was ranked the fourth most important variable, which might seem as an unexpected result when considering its statistically insignificant impact in the multiple regression analysis. In Model II 'space' variable dropped in rank to seventh place; however, this was the only variable that could not be hierarchically ordered by the complete dominance criterion. Only 'apartmentization' and 'appearance' completely dominated 'space' variable, but the latter variable did not dominate any of the other variables. This could be at least partially explained by the relationship of 'space' with the two most important predictors – if 'apartmentization' and 'appearance' were excluded from the model (which would cause confounding or omitted variable bias), the 'space' variable would be the most important predictor in the model, with the largest average contribution. From the qualitative analysis of complete dominance for model II, we can conclude that the most important variables are 'apartmentization' and 'appearance', followed by the second-order variables that are worthy of consideration: 'authenticity', 'services', 'Factor1: Social crowding' and 'Factor4: Housing affordability'. The least important variables are 'Factor3: Current expenses', 'Displacement' and 'Factor2: Waste and cleanliness'. The performance of 'space' variable is more complex which was further inspected in the predictive modeling with random forest approach.

Table 5. Results of dominance analysis

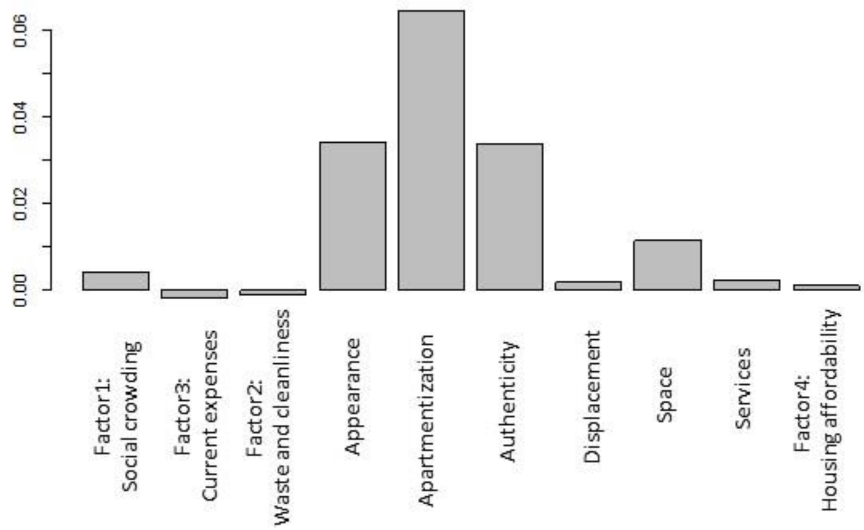
Variable	**Model I**			**Model II**		
	Complete dominance	Average contribution (General dominance)	Rank	Complete dominance	Average contribution (General dominance)	Rank
Apartmentization	1	0.088	1	1	0.088	1
Appearance	1	0.086	2	1	0.085	2

Authenticity	2	0.048	3	2	0.034	3
Space	?	0.029	4	?	0.022	7
Services	?	0.026	5	2	0.024	6
Factor1: Social crowding	?	0.025	6	2	0.027	4
Factor4: Housing affordability	?	0.019	7	2	0.026	5
Factor3: Current expenses	?	0.009	8	3	0.003	10
Displacement	?	0.008	9	3	0.012	8
Factor2: Waste and cleanliness	?	0.008	10	3	0.007	9

4.4. Predictive modeling with random forests

The variable importance rank was determined as the average variable rank obtained from random forest models built under different hyperparameter settings. The results are in line with the dominance analysis and suggest that 'apartmentization' is the most important predictor for overall perception of tourism, followed by 'authenticity' and 'appearance' (Figure 1). The ranking for these three variables is stable under all models estimated. On the other hand, variables 'space', 'Factor1: social crowding', 'services' and 'Factor4: housing affordability' are exhibiting variability in importance ranking across different models, with mean ranks from 4 to 7, respectively. The group of variables having the lowest importance comprises of 'Factor3: current expenses', 'displacement' and 'Factor2: waste and cleanliness'.

Figure 1. Results of unconditional random forest analysis – mean importance of variables



5. Discussion and conclusions

We have presented a statistical framework for risk factor modeling and relative importance analysis in the context of socio-economic assessment of tourism impacts that enhances interpretability and enables prioritization among social indicators of tourism sustainability. The prioritization is achieved by estimating the relative importance of risk factors based on the combination of explanatory and predictive modeling. We have detected particular risk factors which are of paramount importance in understanding the overall perception of tourism and thus should be considered priorities in managing socio-economic impacts of tourism.

Compared to the results of descriptive analysis (Table 1), the presented framework provides completely different insight into underlying risks of tourism development. The descriptive statistics outline the prevalence of perceived negative impacts associated with increases in prices and crowding-related problems. However, as our analysis has shown, these are not the primary issues for sustainable destination development. On the other hand, 'appearance' was the lowest ranked variable in terms of prevalence of negative perceptions in the descriptive analysis, but was among the top two most important predictors in risk modeling. This indicates that statistical analysis of perceptions of tourism impacts should go beyond a simple data analysis and employ more complex models that can support better understanding of the relationships between theoretical measures.

As our findings have confirmed, predictive modeling can capture complex relationships that could be missed in explanatory models. The variable 'space' is the most strongly correlated with the key risk factors ('apartmentization', 'appearance' and 'authenticity'), which explains its non-significant effect in the multiple logistic regression model in contrast to the simple regression model. Although this variable was not identified as a risk factor, it would be inappropriate to conclude that 'space' is not an important predictor of overall perception of tourism. Dominance analysis and random forest models confirm that 'space' is indeed an important predictor. The inconsistency between the explanatory regression analysis and dominance analysis or random forest models should not be surprising considering their different goals. Standardized regression coefficients provide information on the effect of a given predictor after accounting for the effects of all other predictors in the model, thereby measuring additional contribution of each predictor in the presence of all other predictors. This is only a part of the information used by methods that examine all subset models, such as dominance analysis, thus providing a more comprehensive analysis of predictor's impact (Azen & Traxel, 2009).

On the other hand, predictive models are known as a black box models since they are not easily interpretable; therefore, explanatory models can provide more confidence in the findings. Rossi et al. (2020) suggested that individual predictors that are significant in multiple regression analysis and have relatively large dominance statistic require increased attention from stakeholders when setting development priorities, while predictors ranked highly in dominance analysis, but not significant in multiple regression model are also worthy of consideration.

The explanatory modeling in multiple regression analysis aims to find a 'true' model which is often operationalized without considering the pattern of relationship between independent variables. Regarding 'Factor2: Waste and cleanliness' we have found evidence of mediation through 'appearance' and 'authenticity' variables – indirect and total effect (but not direct effect) of Factor2 on the overall perception of tourism were statistically significant after modeling the mediation process (according to the method of Hayes, 2018). Mediator variable can explain the relationship between the two other variables when there is not obvious direct relationship between them. Such indirect effects are easily missed in a regression analysis. However, mediation requires strong theoretical basis and reliance solely on statistical criteria is not adequate.

A low relative importance of 'displacement' might be somewhat unexpected, but a few considerations may at least partly explain this finding. Firstly, acknowledged displacement might not be experienced by the respondent himself/herself, but by the respondent's family or friends. Displacement might also have different causes, e.g. voluntary displacement to realize profits from rental accommodation, or displacement due to impaired quality of life near the main tourist attractions. Insignificant interaction effect between the displacement and realizing (or not) profits from tourism suggests that this variable warrants further research. It might also be possible that displaced residents have successfully adapted to their new living conditions.

Evaluating changes in social situation depends on the social perspectives and values of the place being assessed (UNWTO, 2023). In other words, thresholds should be primarily data-driven. Our framework provides standardized methodology to prioritize monitoring of social sustainability indicators, but enables customization of relevant indicators and thresholds, which are inherently data-driven. The findings suggest that tourism stakeholders in the city of Split should focus their monitoring efforts particularly on 'apartmentization', 'appearance', but also on 'authenticity' and 'space' dimensions of tourism impacts. These are the most important risk factors that have a strong association with overall evaluation of tourism impacts and therefore should be carefully managed to retain or enhance support for tourism development.

Our analysis has some limitations. The sample size of a typical resident survey conducted at the local scale might be somewhat limited for predictive modeling which generally requires larger sample size than explanatory models, especially when dividing the data into a training set and a holdout (test) set to evaluate the prediction accuracy on a holdout data and thus avoid overfitting. Furthermore, using factor analysis to reduce the dimensionality of data and avoid multicollinearity problems is a common practice in statistical analysis. However, dimensionality reduction does not facilitate detailed analysis of individual variables, which might be a serious limitation in the context of risk factor modeling. Factor1 to Factor4 are latent constructs associated with crowding and prices. Future research should inspect the best way to operationalize these constructs, e.g., which individual items/measures or response scales to use, as well as the appropriate procedures to examine the significance and importance of individual items.

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References

Ahn, B., Lee, B., & Shafer, C. S. (2002). Operationalizing sustainability in regional tourism planning: an application of the limits of acceptable change framework. Toruism Management, 23(1), 1-15.

Assaf, A. G., Tsionas, M., & Tasiopoulos, A. (2019). Diagnosing and correcting the effects of multicollinearity: Bayesian implications of ridge regression. Tourism Management, 71, 1-8.

Azen, R., & Budescu, D. V. (2003). The Dominance Analysis Approach for Comparing Predictors in Multiple Regression. Psychological Methods, 8(2), 129-148.

Azen, R., & Traxel, N. (2009). Using Dominance Analysis to Determine Predictor Importance in Logistic Regression. Journal of Educational and Behavioral Statistics, 34(3), 319-347.

Budescu, D. V. (1993). Dominance Analysis: A New Approach to the Problem of Relative Importance of Predictors in Multiple Regression. Psychological Bulletin, 114(3), 542-551.

Bursac, Z., Gauss, C. H., Williams, D. K., & Hosmer, D. W. (2008). Purposeful selection of variables in logistic regression. Source Code for Biology and Medicine, 3:17.

Camatti, N., Bertocchi, D., Caric, H., & van der Borg, J. (2020). A digital response system to mitigate overtourism. The case of Dubrovnik. Journal of Travel & Tourism Marketing, 37(8–9), 887–901.

CBS (2022). Census 2021. Zagreb: Croatian Bureau of Statistics.

Garcia, F. A., Vazquez, A. B., & Macias, R. C. (2015). Resident's attitudes towards the impacts of tourism. Tourism Management Perspectives, 13, 33–40.

Garver, M. S., & Williams, Z. (2019). Utilizing relative weight analysis in customer satisfaction research. International Journal of Market Research, 62(2), 1-18.

Gossling, S., McCabe, S., & Chen, N. C. (2020). A socio-psychological conceptualisation of overtourism. Annals of Tourism Research, 84, 102976.

Hayes, A. F. (2018). Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. New York: The Guilford Press.

Hosmer D. W., & Lemeshow, S. (2000). Applied Logistic Regression. New York: Wiley.

Kim, K., Uysal, M., & Sirgy, M. J. (2013). How does tourism in a community impact the quality of life of community residents? Tourism Management, 36, 527–540.

Klanjšček J., Geček S., Marn N., Legović T., & Klanjšček T. (2018). Predicting perceived level of disturbance of visitors due to crowding in protected areas. PLoS One, 13(6), e0197932.

Matečić, I., Kesar, O., & Hodak, D. F. (2022). Understanding the complexity of assessing cultural heritage's economic impact on the economic sustainability of a tourism destination: the case of Split, Croatia. Ekonomska misao i praksa, 31(2), 639-662.

Mihalic, T. (2020). Conceptualising overtourism: A sustainability approach. Annals of Tourism Research, 84, Article 103025.

Neuts, B., Nijkamp, P., & Van Leeuwen, E. (2012). Crowding externalities from tourist use of urban space. Tourism Economics, 18(3), 649–670.

Rossi, J., Woods, T., & Davis, A. (2020). Resident perspectives on local food system performance and development priorities: A pilot analysis of the local food vitality index. Local Development & Society, 1:2, 116-139.

Shmueli, G. (2010). To Explain or to Predict? Statistical Science, 25(3), 289-310.

Strobl, C., Boulesteix, A.-L., Kneib, T., Augustin, T., & Zeileis, A. (2008). Conditional variable importance for random forests. BMC Bioinformatics, 9:307.

TRAN. (2018). Research for TRAN committee - Overtourism: Impact and possible policy responses. Brussels: TRAN Committee, European Parliament.

Uysal, M., Sirgy, M. J., Woo, E., & Kim, H. L. (2016). Quality of life (QOL) and well-being research in tourism. Tourism Management, 53, 244–261.

Woo, E., Kim, H. L., & Kim, Y. G. (2022). Touristification phenomenon and support for tourism development. Anatolia, 33(1), 65–78.

World Tourism Organization (UNWTO) (2023). Statistical Framework for Measuring the Sustainability of Tourism (SF-MST). Draft prepared for Global Consultation October 2023. Madrid: UNWTO.