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A review of regression analysis methods: Establishing the quantitative relationships between subjective soundscape assessment and multiple factors

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ABSTRACT

Soundscape research has long been exploring factors/indicators that would impact human perception, emotional assessment, behaviour, etc. Since soundscape is intrinsically a complex system, a wide variety of factors have been suggested by intensive studies and also ISO/TS 12913-2 standard, ranging from acoustics, psychoacoustics, sound source composition, to demographics, and other personal/social/cultural factors. To examine subsequently the quantitative relationships between such factors and impacts/effects of soundscape, data statistical methods are essential. A wide range of statistical methods have been commonly used in soundscape studies corresponding to different specific research tasks, e.g. correlation analysis, analysis of variance, factor analysis and cluster analysis. While soundscape is affected by not only any single factor but multiple factors simultaneously and interactively, this paper focuses on a statistical method, regression analysis, that can investigate multiple variables to study the relationships and predict soundscape effects from multiple possible factors. This paper provides a brief review of a set of regression analysis methods, which are used for analysing different types of variables, e.g. continuous, ordinal and nominal. It then exemplifies the methods with a number of regression models from previous soundscape studies, particularly on subjective soundscape assessments (namely soundscape descriptors, e.g. pleasantness, satisfaction, and comfort), which is a crucial part in soundscape research.

Keywords: Soundscape, Regression analysis, Multiple variables

1. INTRODUCTION

Soundscape research has suggested that sound environments have impacts on human perception, cognition, emotion, behaviour, health and well-being, etc. (1). Soundscape studies investigated such impacts/effects due to different sound environments (2). For example, a large number of soundscape studies focused on people's subjective perceptual and emotional responses/assessments of sound environments, such as pleasantness, satisfaction, and comfort, which were defined as soundscape descriptors in ISO/TS 12913-2 standard (3), and formed a substantial part of soundscape research.

The effects of sound environments would be caused by a wide variety of environmental factors, as well as human factors that might explain the individual differences in responses. The factors, explored by previous soundscape studies and suggested by ISO/TS 12913-2 standard (3), include acoustic and psychoacoustic indicators (e.g. equivalent sound pressure level LAeq and LCeq, percentage exceedance levels LA5 and LA95, psychoacoustic loudness, sharpness, tonality, roughness, and fluctuation strength) (4), sound source compositions, visual factors of environment, demographic factors (e.g. age and gender) and other personal/social/cultural factors.

Soundscape research attempts to establish the relationships between the soundscape effects and factors, to study the influences of the factors on various soundscape effects, or to predict soundscape effects/responses from the factors (e.g. use indicators to predict soundscape descriptors). To achieve these in a quantitative way, data statistical methods are essential. A wide range of statistical methods have been used in soundscape studies according to different specific research tasks, e.g. correlation analysis, analysis of variance, factor analysis and cluster analysis. Since soundscape is intrinsically a complex system, effects of sound environments are caused by not only any single factor but multiple factors simultaneously and interactively. To study such relationships, statistical methods that can deal

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with multiple variables need to be used.

Among the statistical methods or machine learning methods that can investigate multiple variables, e.g. regression analysis, fuzzy logic model and artificial neural network, this paper focuses on regression analysis which have been commonly used in soundscape studies. The following of this paper firstly discusses the types of variables (for both impacts and factors), and then provides a brief review of the regression methods for analysing the different types of variables. Finally, it exemplifies the methods with a number of regression models of subjective soundscape assessments, namely soundscape descriptors, from previous soundscape studies.

2. SOUNDSCAPE VARIABLES (E.G. DESCRIPTORS AND INDICATORS)

In statistics, a *variable* is something that varies between individuals or items. All the soundscape impacts and factors can be variables. The variables to be studied or predicted by other variables are called *dependent variables*, frequently the soundscape impacts or soundscape descriptors. The variables used as factors to predict the dependent variables are called *independent variables*, frequently the acoustic and psychoacoustic indicators or other soundscape descriptors. Statistical methods attempt to analyse the relationships between variables or the effects of independent variables on dependent variables.

There are several types of variables, in general categorical and numeric. *Categorical variables* are also known as discrete or qualitative variables. Categorical variables can be further categorised as either binary, nominal, or ordinal. *Binary* or *dichotomous variables* are variables which have only two categories or levels, such as true/false, yes/no (coded by an indicator variable 1/0). *Nominal variables* are variables that have two or more categories, but which do not have an intrinsic order. *Ordinal variables* are variables that have two or more categories just like nominal variables only the categories can also be ordered or ranked. Numeric variables are also known as quantitative variables, and are either discrete or continuous. *Discrete variables* can take only a distinct number of values, often integers for such as count. *Continuous variables* can take any real value number within a certain range, either interval or ratio. There are overlaps between the different types of variable, e.g. there may be dispute about whether an integer variable is discrete numeric or ordinal. In addition, variables can sometimes be deliberately rearranged from one type to another, e.g. age (continuous variable) can be changed to age group (ordinal variable) (5).

Table 1 gives some examples of the types of variables used in soundscape research. It is worth noting that in some cases, variables can be treated as different types. The choice of the type of a variable somehow depends on the case.

Table 1 – Examples of variable types in soundscape research

		Continuous	Categorical		
		Interval/ratio	Binary	Nominal	Ordinal
Soundscape descriptors (e.g. by semantic differential)	11-point / 7- point	•			
	5-point				•
Acoustic and psychoacoustic indicators	LAeq / LCeq / LA5 / LA95 / loudness/ sharpness / tonality / roughness / fluctuation strength	•			
Sound source compositions	Whether a source present or not		•		
	Perceived loudness of a source				•
Demographic factors	Age group				•
	Gender		•		
	Profession			•	

3. STATISTICAL METHODS: REGRESSION ANALYSIS

Regression analysis is a set of statistical methods that estimate the relationship between dependent variables (Y) and independent variables (X). It produces a function of one or more independent variables (with the parameters) called the regression function or regression model, to estimate the dependent variable(s). Regression analysis can be used for indicating the effects of independent variables on dependent variables, finding the causal relationship between the variables, and predicting the dependent variables given the independent variables. Regression analysis is one of the fundamental algorithms in the field of machine learning (6).

The following describes a number of regression methods that have been or would be used in soundscape research, according to the number and type of variables.

3.1 Linear Regression

Linear regression is one of the most widely used regression analysis in practical applications. Linear regression specifies that the dependent variable is a linear combination of the parameters (but need not be linear in the independent variables). The case of one independent variable is called *simple linear regression*. When there are more than one independent variable or function of independent variable(s), it is called *multiple linear regression*.

Linear regression attempts to establish a relationship between a dependent variable and one or more independent variables by fitting a linear equation (e.g. a straight line) to observed data. The equation is in the form Y=a+b*X, where a is the intercept (a constant term) and b is the slope of the line.

The regression can be understood simply as finding the parameters of the equation that best fit the observed data. The most common method for calculating the best-fitting line for linear regression is the method of least squares. This method obtains parameter estimates by minimizing the sum of squared residuals of all data, where the residual is the difference between the predicted value of the dependent variable by the model and the true value of the dependent variable (6).

In linear regression, the dependent variable is continuous, whereas independent variable(s) can be continuous or discrete, such as binary, nominal or ordinal.

3.2 Logistic Regression

Logistic regression (also called logit regression) is a regression analysis in its basic form used for predicting a binary dependent variable rather than a continuous dependent variable in linear regression. Logistic regression calculates the probability of dependent variable being a case or being a non-case (7).

As a generalized linear regression, what logistic regression does is to convert a binary dependent variable into a continuous one, and simulate the continuous one through a linear regression. To do this, logistic regression takes the logit function log[p/(1−p)], where p is the probability, (i.e. the logarithm of the odds (log-odds) where the odds are defined as the probability of being a case divided by the probability of being a non-case), to create a continuous criterion as a transformed version of the dependent variable, and then calculates the log-odds through a linear combination of one or more independent variables. After that, it converts the predicted value of the log-odds back into predicted probability via the inverse of the logit function, namely a logistic function (a sigmoid function), and outputs a value between zero and one. The regression parameters are usually estimated using maximum likelihood estimation.

The logistic regression model itself simply calculates probability of output, and does not perform statistical classification, though by choosing a cut-off value of probability it can be used to make a classification.

The *binomial* or *binary logistic regression* has extensions to more than two levels of the dependent variable: categorical outputs with more than two values are modelled by *multinomial logistic regression*, and if the multiple categories are ordered, by *ordinal logistic regression*.

Like other forms of regression analysis, the independent variables of logistic regression can each be either continuous or categorical.

3.3 Probit Regression

Analogous to logistic regression, probit regression is also used to predict a binary dependent variable. However, probit regression and logistic regression use different link functions (sigmoid functions) to transform the binary dependent variable into a continuous latent variable. Instead of the logit function in logistic regression, probit regression uses an inverse standard normal distribution of probability and models the latent variable as a linear combination of independent variables.

3.4 Multivariate Regression

Unlike the regression methods above which predict one dependent variable, multivariate regression is a regression method of modelling multiple dependent variables. It estimates the relationship of the independent variables with each dependent variable, in a similar way to regressing each dependent variable separately.

4. PREDICTION MODELS OF SUBJECTIVE SOUNDSCAPE ASSESSMENTS

Among various soundscape effects, such as perception, emotion, behaviour, health and well-being, a number of regression models of subjective perceptual/emotional assessments (as a substantial part in soundscape research) from previous soundscape studies are presented in this section, as application examples of the above regression analysis methods.

4.1 Multiple Linear Regression Model

4.1.1 Sound Quality in Terms of Pleasantness

Ricciardi et al (8) used multiple linear regression to model the perceived sound quality (pleasantness) of soundscape from other perceptual variables. They collected perceptual data from a large number (3409) of participants in Paris via smartphone applications. When a participant visited a defined location at a defined time (with the GPS and time information recorded on the mobiles), the sound pressure levels were recorded and the participant answered a questionnaire covered question items in three categories based on 11-point bipolar semantic scales. The first category was related to the overall sound environment: Overall loudness (OL), which described the perceived sound level of the sound environment at the location, from “quiet” to “loud”; Liveliness (L), from “lifeless” to “lively”; Not enveloping (NE), from “enveloping” to “not enveloping”, Sound quality (SQ), from “unpleasant” to “pleasant”; Visual amenity (VA), from “unpleasant” to “pleasant”, and Familiarity (F), from “unfamiliar” to “familiar”. The second category described the emergent sound sources: perceived loudness of such as mopeds (PLM), cars (PLC), horns and sirens (PLH), trucks (PLT) and buses (PLB), from “low” to “high”. The third category of parameters dealt with the time of presence of sound sources such as traffic (T), voices (V), footsteps (F), birds (B), water (Wa) and wind (Wi), from “rarely present” to “continuously present”.

They treated all the variables as continuous and built multiple linear regression models to predict the perceived SQ (sound quality) from the other perceptual variables. They obtained:

$SQ = 4.48 + 0.52VA – 0.27OL + 0.12V – 0.12T$ ($R^2_{adj}=0.52$)

The results showed that the predicted sound quality explained 52% of the variance of the real perceived sound quality. A correlation of 0.72 (r=0.72) was obtained between them.

Without visual amenity, they obtained:

$SQ = 8.11 − 0.38OL − 0.14T + 0.20V + 0.15B$ ($R^2=0.34$)

Based on the regression method, they found the factors including perceived loudness of global sound environment and the presence time ratio of certain sound sources (traffic, voices, and birds) that did not emerge from the background noise significantly influenced the perceived sound quality, and could be used to predict sound quality in urban context to a certain extent according to the collected data.

Later, using similar question items on 11-point bipolar semantic scales, Aumond et al (9) collected the subjective assessments from 37 participants (in four groups) during an urban soundwalk, at different locations along a walk path. Simultaneously, instantaneous 1/3-octave band sound levels and audio signals were recorded.

Again, they performed multiple linear regression (with stepwise optimization) to model the pleasantness (P) (similar to sound quality above since using the same bipolar semantic scales) using perceptual parameters. They obtained:

$P = 9.70 − 0.47OL − 0.21T + 0.12V + 0.09B$ ($R^2=0.58$)

The predicted pleasantness explains 58% of the pleasantness variance, and 90% ($R^2=0.90$) of the part pleasantness variance due to the change of sound environment (examined by a multilevel analysis).

Further, they calculated a large set of acoustical indicators from the sound measurements, including sound pressure level (L), Zwicker loudness (N), dispersion parameters (e.g. L10-L90, N10-N90), standard deviation of sound pressure level, spectrum centre of gravity, number of noise events, normalised time and frequency second derivative (TFSD) (which characterised tonal or harmonic sounds such as voices or birds), and spectral flatness deviation. Then, they proposed multiple linear regression model to estimate pleasantness based on the most relevant acoustical indicators:

$P = 16.48 - 0.25L_{50,1kHz} + 15.82TFSD_{mean,500Hz} + 16.82TFSD_{mean,4kHz(1/8s)}$ (R^2=0.48)

The model explains 48% of the pleasantness variance, and 85% (R^2=0.85) of the part pleasantness variance due to the change of sound environment.

4.1.2 Tranquillity

Pheasant et al (10, 11) conducted a series of laboratory studies and used multiple linear regression to examine the effects of soundscapes and visual features on the perception of tranquillity of environments. They presented audio and visual recordings captured from 11 English rural and urban landscapes to 44 volunteers in laboratory. Then, they collected the subjects' subjective assessments of perceived tranquillity of each location on a 11-point scale, and the perceived loudness of five generic soundscape components, i.e. human (H), mechanical (M), biological (B), weather (WX), and water (WA), on a 5-point verbal scales ("sound source not present", "quiet", "moderately quiet", "moderately loud", and "loud").

By including measured L_{Aeq}, L_{Amax}, L_{Amin}, L_{A90}, L_{A10} of the audio recording, the percentage of visual natural features (NF) in visual recording, and the perceived loudness of the soundscape components in each location as independent variables, they proposed multiple linear regression models of tranquillity (TR) as Tranquillity Rating Prediction Tool (TRAPT). Similarly, the perceived tranquillity on a 11-point scale was treated as a continuous dependent variable.

For the audio only experimental condition (with uni-modal auditory stimuli), the prediction equations are:

$TR = 9.99 – 0.93L_{Amax} – 0.45PLM + 1.16PLB$

or

$TR = 7.74 – 0.67L_{Aeq} – 0.53PLM + 1.19PLB$

where PLM is the perceived loudness of mechanical sounds and PLB is the perceived loudness of biological sounds.

For the audio-video experimental condition (with bi-modal auditory-visual stimuli), the equations are:

$TR = 13.93 - 0.165L_{Amax} + 0.027NF$ (R^2=0.52)

or

$TR = 8.57 + 0.036NF - 0.11L_{Aeq}$ (R^2=0.49)

The results showed that among the factors examined, L_{Amax} or L_{Aeq}, and perceived loudness of mechanical sounds and biological sounds mostly affected the perceived tranquillity in the audio only condition, and L_{Amax} or L_{Aeq}, and percentage of visual natural features in the audio-video condition.

4.2 Multinomial Logistic Regression Model

In in-situ questionnaire surveys in green spaces of Cáceres, Spain, Rey Gozalo et al (12) collected satisfaction assessments of a random sample of 182 adult visitors. They collected each visitor's overall satisfaction with the green spaces, as well as specific satisfactions with the features of cleanliness, air quality, noise, aesthetics, safety, users, conservation, location, size, groves, and shade, all of which were rated on a 5-point Likert scale from "nothing satisfied" to "very satisfied".

They treated the variables as categorical and used multinomial logistic regression (with stepwise selection) to study the influence of the specific satisfactions on the overall satisfaction. The likelihood ratio showed the satisfactions of noise, users, conservation, and shade features contributed significantly to explaining the overall satisfaction. The regression model generated a McFadden R^2 of 0.41, which was considered to have an excellent fit quality. The model could correctly predict 71.4% of the cases.

4.3 Binomial Logistic Regression Model

Tse et al (13) used binomial logistic regression to predict the acoustic comfort evaluation of urban parks from multiple factors and investigate the relative impacts of the factors. They conducted in-situ questionnaire surveys with 595 random users in four public parks in Hong Kong. Sound recordings and sound level measurements were carried out at the survey spots concurrently. They collected users' responses on subjective perceived sound strength/level (SUB) ("very quiet," "quiet," "adequate," "noisy," and "very noisy"), acoustic comfort ("very uncomfortable," "uncomfortable," "neutral," "comfortable," and "very comfortable") of soundscape, visual comfort of landscape (LAND), preference for natural sounds (PREFN), preference for anthropogenic and mechanical sounds (PREFH) (“very much dislike,” “dislike,” “neutral,” “like,” and “very much like”) on 5-point verbal scales, and whether they could hear a particular type of sound from a list of sounds (including sounds from insects (INSECT), bird (BIRD), tree (TREE), water flow (FLOW), wind (WIND), bike (BIKE), light vehicles (LIGHT), heavy vehicles (HEAVY), talking (TALK), screaming (SCREAM)), as well as age group (AGE), gender (GENDER), residency status (RESI), duration of stay in a park (DUR), and self-rated auditory sensitivity (AUDIT) (“very bad,” “bad,” “neutral,” “good,” and “very good”). They also calculated the acoustic indicator of L_{Aeq} (LEQ) from the sound measurements.

Then, to focus on only high or low acoustic comfort evaluation, they dichotomized the variable of perceived acoustic comfort originally rated on a 5-point verbal scale into binary variable, i.e. “low acoustic comfort”, referring to a rated response of very uncomfortable, uncomfortable, or neutral, and “high acoustic comfort”, referring to a rated response of comfortable or very comfortable. Other factors, with an exception of continuous variables such as L_{Aeq}, were also dichotomized in the same manner. Consequently, they formulated a binomial logit model for predicting the acoustic comfort evaluation from the multiple factors studied, and then investigated the relative impacts of the factors through the model.

The results showed a McFadden’s R^2 value of 0.26 for the logit model. Based on the model, both objective and subjective sound level, existence of sounds from breeze, bikes, and heavy vehicles, visual comfort of landscape, residency status, preference for natural sounds, and preference for anthropogenic and mechanical sounds, among the various factors, were found to significantly influence the acoustic comfort evaluation.

5. SUMMARY

The above research studies show that regression analysis is a useful statistical method to study the relationship between soundscape effects/descriptors and factors (especially for multiple factors). It can be used to find the factors that significantly affect the soundscape effects/descriptors from a set of possible factors and produce models to predict the descriptors given the significant multiple factors.

A number of regression methods are available for analysing different types of dependent variables. Table 2 gives a summary of the regression methods frequently used for the different dependent variable types. If a dependent variable is continuous, e.g. a soundscape descriptor rated in a 11-point scale, multiple linear regression can be used (8-11). If ordinal, e.g. a soundscape descriptor rated in a 5-point scale, ordinal logistic regression can be used. In certain cases, a continuous or ordinal variable, e.g. a soundscape descriptor rated in a 5-point scale, can be also treated as nominal (12) or dichotomized into binary (13) according to the specific need of research, for which multinomial logistic regression or binary logistic regression can be used respectively.

Table 2 – Regression methods for different types of dependent variables

		Continuous	Categorical		
		Interval/ratio	Binary	Nominal	Ordinal
Linear regression	Simple linear regression	•			
	Multiple linear regression	•			
Logistic regression	Binary logistic regression		•		
	Multinomial logistic regression			•	
	Ordinal logistic regression				•

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