Visual Quality Preference: the Smyser Index Variables

Jon Bryan Burley, and Rüya Yilmaz

***Abstract*—** For the past fifty years, planners, designers, scientists, citizens and government officials have been interested in predicting respondent's perceptions concerning the environment. One of the breakthroughs in understanding respondent preference was the development of a twenty variable index that included ecological, functional, and cultural requirements, an index adapted from C. Smyser. Before that time, investigators primarily examined aesthetic variables. In our study, we examined this index in detail, separating the variables from the index into main effects and squared terms. Initially, we discovered that only a portion of the variables actually contribute to respondent preference, producing a new prediction equation which explains over 80% of North American and European respondent preference for landscapes. We then generated first order interaction terms as variables and produced lengthy equations that could explain about 98% of the variance. These highly predictive but longer equations are similar in length to equations that predict GNP.

***Keywords*—**Criteria analysis, regression analysis, landscape assessment, environmental psychology, landscape architecture, environmental design, people and environment, social science.

I. Introduction

DEVELOPMENTS in predicting respondent preference has made progress in the last fifty years. Mo et al., describes much of this progress [1]. Predictions concerning the quality of the environment originated as expert models and non-statistical indexes employing the spatial theory practiced by planners and designers. Then scholars began employing statistical techniques. Initial equations would often only predict 30% of the variance. As more variables were tested and examined, the equations improved. In addition, scholars discovered that respondent reactions to photographs co-varied with responses to actual landscapes. Recently, Partin *et al*., have demonstrated that computer 3-D models are a reliable substitute for photographs and that respondents evaluate the digital images as being comparable to photographs [2]. Lu *et al*., was able to construct a validated visual quality map of a study area in Michigan, meaning that it is possible to construct maps of visual quality that are reliable [3]. The equations developed by investigators such as Burley *et al*. represent the state of the art concerning the complexity of prediction equations and the ability to explain about 75% of the variance in the variables [4]. They employed their study to examine differences in spatial treatments for the city of Detroit. Investigators have also been examining the abstract fractal pattern of images to predict the perceived quality of the image [5].

Burley's *et al*., equation was composed of variables presented in Table 1 and defined in Table 2 [4]. The environmental quality index is represented in the equation by the variable CVQ. This index is presented in Table 3 and is composed of 20 items. Most of the variables in the index were proposed by C. Smyser [6]. Liu and Burley recently studied the ordination and range of such variables by some North American respondents [7]. They discovered the actual range may be 30 or more independent and orthogonal variables. In other words, the Smyser Index is not an exhaustive list of variables and there is the potential to add other variables to the list.

Table 1. Regression modeling results.

Variable	Estimate	Pr > F
Intercept	58.98827	<.0001
V2	0.07725	<.0001
V10	0.03775	<.0001
CVQ	−1.18505	<.0001
V32	−0.01074	<.0001
V52	0.01161	0.0002
V1V2	−0.00181	0.0002
V1V5	−0.00026	0.0041
V1V10	0.00134	0.0277
V2V14	−0.00071	0.0009
V5V9	0.00018	0.0080
V7V18	−0.00092	0.0065
V8V14	0.00025	0.0145
V8V15	0.00425	0.0004
V15V18	0.00023	0.0272
V2V32	−0.00012	0.0135
V6V34	6.13388E − 7	0.0369
V8V34	−7.8380E − 7	0.0423
V11V52	0.00117	0.0012

The CVQ variable was of interest, because it included sub-variables that are often not examined in visual quality studies. Usually such studies examine aesthetic predictors such as the spatial relationship between foreground, mid-ground, and

Manuscript received January 2014

Dr. Jon Bryan Burley is in the Landscape Architecture Program, at the School of Planning, Design, and Construction, College of Social Science and College of Agricutlrue and Natural Resources, Michigan State University, E. Lansning, MI, 48824, USA (001-989-682-4284; e-mail: burleyj@msu.edu).

Dr. Rüya Ylimaz is an associate professor at Namk Kemal University in the Department of Landscape Architecture, of the Fine Arts, Design and Architeture Faculty, 59030 Tekirda/Turkey (e-mail: ryilmaz@nku.edu.tr).

background features, mystery, and openness [1]. The CVQ index includes ecological, functional, economic, and cultural inputs. The success of the CVQ index as a predictor has led to investigators claiming that respondents examine the landscape holistically making judgments about the environmental that are more than just aesthetic. The claim makes some common sense and helps to explain how culture, ecology, and economics are values that influence environmental perception. In 2005, this discovery was considered a breakthrough in understanding landscape preference.

Table 2. Definition of variables in Table 1.

Variable	Description
CVQ=	environmental quality index
V1=	perimeter of immediate vegetation
V2=	perimeter of intermediate non-vegetation
V3=	perimeter of distant vegetation
V4=	area of intermediate vegetation
V5=	area of water
V6=	area of distant non-vegetation
V7=	area of pavement
V8=	area of building
V9=	area of vehicle
V10=	area of humans
V11=	area of smoke
V14=	area of wildflowers in foreground
V15=	area of utilities
V16=	area of boats
V17=	area of dead foreground vegetation
V19=	area of wildlife
V30=	open landscapes V2 +V4 + (2*(V3+V6))
V31=	closed landscapes V2 +V4 + (2*(V1+V17))
V32=	openness V30-V31
V34=	mystery V30*V1*V7/1140
V52=	noosphericnessV7+V8+V9+V15+ V16

While Burley and Mo have indicated that this variable (CVQ in Table 1) is a significant predictor, the dissection of the variable has not been undertaken until recently [1, 4, 8]. We were interested in studying each separate variable in Table 3 and understanding the contribution that each variable may contribute to an overall equation. We were concerned that the index was redundant and over-specifying the contribution of the group of variables within the index

We wondered if all of the variables were necessary and possibly only a few were contributing to the prediction models and we wondered if it was possible to create an improved model by dissecting the parts. For our study we desired to examine the main effect terms and the squared terms of the index. We were interested in examining the possible first order interaction terms that are associated with the variables in Table 3. Since 1997 investigators have stated this index is a strong predictor, yet no investigator had examined its parts. We believed it was time to develop a closer examination of the variables in Table 3 to determine which variables were redundant or explained nothing. Our intent was to see if a better model could be generated that explained a great proportion of the variance by the respondents. We also understood that the construction of such models could lead to longer and more complex equations such as those found in econometric forecasting, as recently illustrated by Mosheim, where equations imbedded within equations form a fairly large prediction model [9].

Table 3. Environmental Quality Index

Variable	Score
A. Purifies Air	+1 0 -1
B. Purifies Water	+1 0 -1
C. Builds Soil Resources	+1 0 -1
D. Promotes Human Cultural Diversity	+1 0 -1
E. Preserves Natural Resources	+1 0 -1
F. Limits Use of Fossil Fuels	+1 0 -1
G. Minimizes Radioactive Contamination	+1 0 -1
H. Promotes Biological Diversity	+1 0 -1
I. Provides Food	+1 0 -1
J. Ameliorates Wind	+1 0 -1
K. Prevents Soil Erosion	+1 0 -1
L. Provides Shade	+1 0 -1
M. Presents Pleasant Smells	+1 0 -1
N. Presents Pleasant Sounds	+1 0 -1
O. Does Not Contribute to Global Warming	+1 0 -1
P. Contributes to the World Economy	+1 0 -1
Q. Accommodates Recycling	+1 0 -1
R. Accommodates Multiple Use	+1 0 -1
S. Accommodates Low Maintenance	+1 0 -1
T. Visually Pleasing	+1 0 -1
Total Score	________

II. Methodology

We utilized the procedures and database from Burley to conduct the study [4]. The respondents were composed of American, Canadian, French, and Portuguese individuals. The basic procedures are well established and published since Burley in 1997 [10]. We decomposed the index into 20 main effect variables, plus the squared terms of each main effect variable, and the first order interaction terms to form new variables to study. We then exposed the variables to regression analysis along with the variables that have been studied in the past by Burley *et al*., searching for the best equation, meaning an equation that explained as much variance as possible and all of the regressors in the proposed equation were significant ($p \leq 0.05$) [4, 9]. To construct the equations, first we tested models with only main effects and squared terms from Table 3, and then we tested models which included first order interactions terms.

III. Results

Firstly, the main effects variable concerning, "does the environment 'preserve natural resources?'" with no intercept component could explain 52% of the variance by respondents. With an intercept component, the prediction equations could explain 58% of the variance. The proportion of variance explained is greater than early statistical equations employing aesthetic variables which may have only explained 30% of the variance [11, 12].

Table 4. Regression results with main effects and squared terms from Table 3

R-Square = 0.8149
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr>F
Model	22	61796	2808.92	36.03	<.0001
Error	180	14034	77.97		
CTot	202	75831			

Variable	Parameter Estimate	F Value	Pr>F
Intercept	61.71363	2686.60	<.0001
E5	-8.08467	73.72	<.0001
E14	-5.54432	23.39	<.0001
E18	3.93871	20.04	<.0001
E20	-5.59630	24.87	<.0001
E4S	4.38969	10.85	0.0012
V2S	0.00041	10.84	0.0012
V32	-0.00901	26.73	<.0001
V1V3	-0.00101	9.38	0.0025
V2V4	-0.00016	10.41	0.0015
V2V6	-0.00038	16.18	<.0001
V2V10	0.0008	10.03	0.0018
V4V10	0.000098	5.26	0.0230
V5V9	0.000213	13.14	0.0004
V6V7	-0.00023	4.43	0.0367
V7V17	0.000414	11.42	0.0009
V7V19	-0.00196	10.96	0.0011
V8V13	0.000113	9.45	0.0024
V8V15	0.00402	15.44	0.0001
V9V15	0.01381	8.32	0.0044
V14V15	0.05315	4.53	0.0347
V14V17	-0.00031	7.96	0.0053
V6V34	0.0000015	12.67	0.0005

Our study of the main effects and squared terms revealed a 22 model variable that explained 81.49 percent of the variance (Table 4). This model explained more variance than many previous prediction models and included variables from the environmental quality index. However, not all of the environmental quality index variables are employed in the model, suggesting that some of the environmental variables are not necessary, redundant, or have no association with predicting environmental/visual quality.

When the interaction terms from Table 3 were employed, the results produced a 99 variable model (Table 5) explaining 98.45% of the variance. Models larger than 99 variables produced equations where at least one of the regressors being not significant ($p \leq 0.05$). In the model represented in Table 5, only *promoting biological diversity* was not represented as a regressor.

Table 5. Regression results with interaction terms from Table 3.

R-Square = 0.9846
Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr>F
Model	99	74664	752.18	66.69	<.0001
Error	103	1166.6	11.33		
CTot	202	72831			

Variable	Parameter Estimate	F Value	Pr>F
Intercept	73.21	2389.72.	<.0001
E5	-2.28	9.45	<.0027
E11	4.81	59.45	<.0001
E14	-11.64	252.88	<.0001
E18	5.57	47.23	<.0001
E19	-2.57	12.95	<.0001
E20	-52.71	27.31	<.0001
E2S	-7.57	70.95	<.0001
E4S	2.64	11.86	0.0008
E5S	3.84	13.79	0.0003
E10S	-5.63	43.93	<.0001
E19S	-4.69	23.64	<.0001
E1E4	-1.47	4.10	0.0454
E1E7	-4.69	16.51	<.0001
E1E12	-2.62	13.39	0.0004
E1E16	-5.27	44.94	<.0001
E1E19	-3.63	27.51	<.0001
E2E3	8.38	148.86	<.0001
E2E7	4.00	10.88	0.0013
E3E7	-3.83	9.24	0.0030
E3E16	7.27	103.42	<.0001
E3E17	-17.49	211.75	<.0001
E4E10	6.15	62.26	<.0001
E4E14	-4.64	35.32	<.0001
E5E14	-6.92	62.26	<.0001
E5E18	3.12	15.02	0.0002
E5E20	5.08	37.46	<.0001

Table 5. Continued.

Variable	Parameter Estimate	F Value	Pr>F
E6E10	-5.47	63.91	<.0001
E7E18	5.96	27.42	<.0001
E9E11	4.61	48.79	<.0001
E9E12	-3.84	40.64	<.0001
E9E13	-7.56	90.84	<.0001
E9E16	3.19	18.56	<.0001
E9E17	5.39	33.31	<.0001
E10E14	2.16	9.95	0.0021
E10E16	-8.87	126.62	<.0001
E11E12	2.58	13.51	0.0004
E11E18	-5.46	54.97	<.0001
E11E19	1.73	7.21	0.0084
E11E20	-4.47	39.57	<.0001
E12E15	2.92	14.15	0.0003
E12E16	-1.42	6.28	0.0138
E13E15	2.65	13.74	0.0003
E14E18	4.35	27.10	<.0001
E14E19	9.29	124.75	<.0001
E16E17	-2.35	8.45	0.0045
E16E19	6.32	82.38	<.0001
E17E18	2.40	8.15	0.0052
E18E19	-7.11	76.37	<.0001
V1	-0.16	41.66	<.0001
V11	0.045	81.24	<.0001
V1S	0.00090	58.96	<.0001
V2S	0.00054	43.11	<.0001
V3S	0.00080	59.60	<.0001
V4S	0.0000076	4.58	0.0348
V5S	-0.000016	58.30	<.0001
V32	-0.014	131.07	<.0001
V52	0.02	90.16	<.0001
V52V34	-0.000000117.47		<.0001
V1V2	0.0008	8.15	0.0043
V1V3	-0.002	111.55	<.0001
V1V4	-0.0001	21.31	<.0001
V1V14	-0.0009	18.13	<.0001
V1V19	0.0037	17.34	<.0001
V2V3	-0.0007	9.24	0.0030
V2V4	-0.0003	58.89	<.0001
V2V8	0.0001	6.25	0.0139
V2V10	0.0015	135.07	<.0001
V2V11	-0.0025	114.80	<.00001
V2V13	-0.00026	48.39	<.0001
V3V18	-0.00031	8.25	<.0050
V4V10	0.00015	55.71	<.0001
V4V18	-0.00020	67.36	<.0001
V4V19	-0.00016	11.99	0.0008
V5V8	-0.00023	130.38	<.0001
V5V18	0.0005	11.99	0.0008
V6V7	-.000040	65.84	<.0001
V6V15	-0.011	12.50	0.0006
V6V17	-0.00014	4.32	0.0401
V7V8	-0.000029	5.19	0.248
V8V15	0.00617	153.23	<.0001

Table 5. Continued.

Variable	Parameter Estimate	F Value	Pr>F
V8V19	-0.00259	26.77	<.0001
V9V10	-0.00007	16.90	<.0001
V9V15	0.01136	19.63	<.0001
V9V18	0.00544	49.44	<.0001
V9V19	-0.1709	123.48	<.0001
V10V17	-0.00219	17.00	<.0001
V14V15	0.09942	26.29	<.0001
V14V17	-0.00021	11.19	0.0011
V18V19	0.00567	44.25	<.0001
V2V32	-0.00010	13.53	0.0004
V14V32	-0.000017	4.05	0.0469
V15V32	-0.00059	6.13	0.0149
V17V32	0.000025	72.41	<.0001
V5V34	-0.000011	29.95	<.0001
V6V34	0.000002	78.52	<.0001
V7V34	0.000001	13.64	0.0004
V15V34	0.01171	152.63	<.0001
V5V52	0.00014	63.06	<.0001
V17V52	0.00039	40.63	<.0001

IV. Discussion

In the study of the main effects and squared term variables, the variables from the environmental quality index include: *preserving natural resources, presents pleasant sounds, accommodates multiple use, visually pleasing*, and the square of *promoting human cultural diversity*. Only increasing scores in preserving natural resources, presents pleasant sounds, and visually pleasing result in an improvement in environmental quality. If each of these variables increase by just one point, the increase in environmental quality is a change in approximately 19 points. A change in accommodating multiple use by one point will change the environmental quality score by about 4 points. This indicates that compared to the other predictors, these variables are relatively strong predictors.

Cultural diversity squared (E4S) is also a strong predictor. However, its interpretation is a bit more difficult, as images with poor cultural diversity and scores with strong cultural diversity both produce less preferred environments. This means that environments that are neutral towards cultural diversity are preferred.

The main effects and squarred term study refutes the implied notion that economic and many functional variables directly affect environmental quality, at least among the variables found in the index. Although most of the remaining unused variables were expressed as interaction terms, and help to support the notion that economic and functional environmental variables are indeed important predictors. From Table 4, five of the Smyser Index variables are significant regressors (from the list of 20): *promotes human cultural diversity* (E4), *preserves natural resources* (E5), *presents pleasant sounds (*E14), *accommodates multiple-use* (E18), and a general *visually pleasing* variable (E20). The general environmental quality index has dropped out of the equation.

The other variables in the equations drift from what Burley had discovered in 1997 to many more interaction terms and fewer main effects terms [10]. Most of these variables have small parameter estimates, meaning that the variables must comprise a large proportion of the image to make large changes in the predicted score.

We find it interesting that sound is a significant regressor. Respondents were not exposed to any sounds associated with the images they were shown. Instead the respondents had to imagine the sounds associated with the images, such as cars, animals, the wind, and people. Yet if pleasant sounds were associated with the image, the image was more preferred (Figure1); and when the image was associated with the sounds of intrusions, the scores became less preferred (Figure 2).

From the results in Table 4, we also wonder why accommodating multiple use rendered images as being less preferred. We believe that this is a line of research that deserves greater inspection. In our results, landscapes that contain a variety of uses are less preferred and landscapes that are simple, with one use are more preferred. The image in Figure 3 might give clues as to why these images are less preferred. Figure 3 is an image where the landscape is used for transportation, water delivery, and scenic/natural beauty. This multiple use landscape image may be in conflict with the expectations of the respondent. Although, the results in Table 5 indicate that multiple-use is a term that interacts with other terms such as preserving natural resources and preserving soil erosion.

Figure 1. Image 117 in Minneapolis, Minnesota, from Burley and from Mo *et al.,* (copyright © 1977 Jon Bryan Burley all rights reserved, used by permission) [1, 10].

Figure 2. Image 127 in southern Minnesota from Burley and from Mo *et al*., (copyright © 1978 Jon Bryan Burley all rights reserved, used by permission) [1, 10].

Figure 3. Image 158 in central Colorado from Burley and from Mo *et al*., (copyright © 1988 Jon Bryan Burley all rights reserved, used by permission) [1, 10].

We were surprised that the variable associated with radioactive contamination was a significant regressor. It was one of the variables added to the initial Smyser Index, just for something for students to thing about [7]. It was not anticipated that this variable would be a regressor. Meanwhile, promoting biological diversity was not a predictor in Table 5. For the strong emphasis placed upon preserving biological diversity by universities, non-governmental organizations, and media, this measure was apparently not in the range of values and responses by the people who were studied.

From our studies with students, there are many other types of variables that could be examined [7]. Our students have suggested that safety, health, physical fitness, walk-ability, transportation ease, religious sensitivity, respect of family, facilitating honesty, and promoting general welfare are other predictors that could be included in future studies. However, the current equation in Table 5 suggests that there is only 1.5% of the variance to be explained. While there are many other variables that could be employed, there is relatively little more to be gained by an improved model.

The improved model, while cumbersome (99 regressors), does have a high degree or predictability. Plots of the 95% confidence tails for this equation range in the $\pm$2% range (Figure 4). Typically, the scores in the images studied range from 30 to 110, where 30 represents images with preferred contents and images with scores near 100 represent least preferred images. Images that score only 4 points different are considered to be perceptually different by the respondents ($p<0.1$). Across an 80 point scale, this means that there are 20 levels of perceptual difference (20=80/4). We believe that these 20 levels represent a fine, somewhat continuous level of differentiation and discrimination amongst a set of environments. Back in the 1990s, the level of differentiation was nearly 10 points. For a range of 80 points, this meant only 10 levels of differentiation amongst images.

The labels of the X-axis in Figure 4 range from natural landscape images which were highly liked containing mountains, flowers, and animals (the Like category), to neutral environments containing green vegetation, water, and sky, to urban environments (somewhat disliked) with buildings, roads, people, and cars, to highly disliked environments with smoke stacks, utility wires, and soil erosion. These preferences are explained in three general theories about respondent preferences. The "Neutral Theory" suggests that common environmental contents such as green plants, sky, and water, where the respondent is in a landscape not inhabited by other humans generates a neutral response. "Intrusion Theory suggests that spaces containing the contents of others (buildings, cars, signs, fences, roads, soil erosion, and related objects) are not preferred by respondents. "Temporal Enhancement Theory" suggests that special preferred objects/experiences such as flowers, animals, pleasant smells, and views of mountains are highly preferred by respondents. In addition, environments that have perceived economic benefits, cultural sensitivity, and environmental stewardship are also preferred.

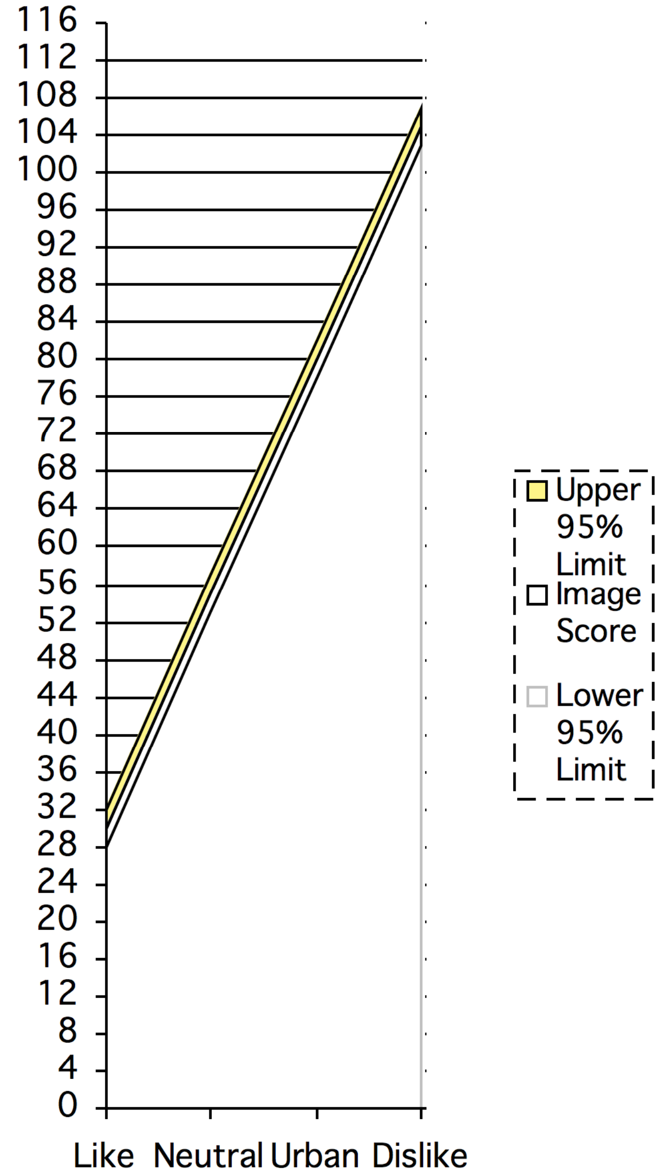

Figure 4. This image illustrates the general predicted upper and lower 95% confidence limits for any image ranging in score from 30 to 105, with approximately 20 levels of differentiation, similar to techniques employed by Burley 1997 [10].

V. Conclusion

Our study suggests that most of variables in the environmental quality index do contribute to explaining the variance of respondents. Only five variables (main effects and squared terms) add to refining the best predictor equation: *promoting human cultural diversity, preserving natural resources, presenting pleasant sounds, accommodating multiple-use*, and a general *visually pleasing* variable. These five variables then modify the contribution of previously studied variables. The equation explains over 80% of the variance in perception. A second equation was produced that explained 98.5 % of the variance. Only *contributing to biological diversity* was not a predictor. Progress has been made from the 1960s where only approximately 35% of the variance could be explained to now, where 98.5% of the variance can be explained. We now understand that highly disturbed and intrusive human environments are not preferred and very natural environments with special attributes are preferred. In addition, environments that are economic beneficial, culturally sensitive, and ecologically sound are also appreciated.

REFERENCES

[1] Mo, F., G. Le Cléach, M. Sales, G. Deyoung, and J.B. Burley, Visual and Environmental Quality Perception and Preference in the People's Republic of China, France, and Portugal, *International Journal of Energy and Environment*, 2011, Vol.4, No.5, pp. 549-556.

[2] Partin, S., J. B. Burley, R. Schutzki, and P. Crawford, Concordance between Photographs and Computer Generated 3D Models in a Michigan Highway Transportation Setting, Buhmann, E., S. Ervin, and M Pietsch (eds.) in: *Peer Reviewed Proceedings of Digital Landscape Architecture 2012 at Anhalt University of Applied Sciences*, Wichmann, 2012, pp. 482-471.

[3] Lu, Di, J.B. Burley, P. Crawford, R. Schutzki, and Luis Loures, Chapter 7: Quantitative Methods in Environmental and Visual Quality Mapping and Assessment: a Muskegon, Michigan Watershed Case Study with Urban Planning Implications, *Advances in Spatial Planning*, InTech, 2012, pp. 127-142.

[4] Burley, J.B., G. Deyoung, S. Partin and J. Rokos. Reinventing Detroit: Grayfields—New Metrics in Evaluating Urban Environments. *Challenges*, 2011 Vol.2, pp. 45-54.

[5] Cooper, J., D. Watkinson, and R. Oskrochi. Fractal Analysis and Perception of Visual Quality in Everyday Street Vistas, *Environment and Planning B: Planning and Design*, 2010, Vol.37, No.5, pp. 808-822

[6] Smyser, C.A. *Nature's Design: A Practical Guide to Natural Landscaping*, Rodale Press, 1982.

[7] Liu, C.Q. and J.B. Burley, Landscape Evaluation Criteria: Dispersed Expectations, *Modern Landscape Architecture*, Proceedings of the 6th WSEAS International Conference on Landscape Architecture (LA'13), Nanjing China, November 17-19, 2013, pp.19-23.

[8] Yilmaz, R. and J. B. Burley., Dissecting the Smyser Index in Visual Quality, *Modern Landscape Architecture*, Proceedings of the 6th WSEAS International Conference on Landscape Architecture (LA'13), Nanjing China, November 17-19, 2013, pp. 32-36.

[9] Mosheim, R., *A Quarterly Econometric Method for Short-term Forecasting of the U. S. Dairy Industry*, United States Department of Agriculture, 2012, Technical Bulletin Number 1932.

[10] Burley, J.B. Visual and Ecological Environmental Quality Model for Transportation Planning and Design, *Transportation Research Record*, 1997, Vol.1549, pp. 54-60.

[11] Taylor, , J. G., E. H. Zube, E. H., J. L. Sell., Landscape Assessment and Perception Research Methods, in *Methods in Environmental and Behavioral Research*, Eds. Bechtel, R. B. et al. Van Nostrand Reinhold Company, 1987, pp. 361-393.

[12] Shafer, E. L., Jr., Perception of Natural Environment, *Environment and Behavior*, 1969, 1,171-82.

Jon Bryan Burley is an associate professor of landscape architecture in the School of Planning, Design and Construction, at Michigan State University. He earned his Bachelor of Landscape Architecture with Distinction at the University of Minnesota in 1978, his Masters of Landscape Architecture from the University of Manitoba in 1988, and his PhD. in Landscape Architecture at the University of Michigan in 1995.

He has been a Fulbright scholar in 2003 at Faro, Portugal and an International Scholar at Agro-campus Ouest, Angers, France, 2011-12. He has published nearly 300 papers in his career, publishing in a variety of topics concerning theory, planning, and design in landscape architecture.

Dr. Burley is a Fellow in the American Society of Landscape Architects, and a life member in the Ecological Society of America, and the American Society for Mining and Reclamation. In 2005 he was awarded the American Society of Mining and Reclamation Researcher of the year. He has won numerous teaching, planning, and design awards.

Rüya Yilmaz is an associate professor in the Department of Landscape Architecture, Fine Arts, Design and Architecture Faculty, Namk Kemal University, Tekirdag, Turkey. She earned a Bachelor of Science in Landscape Architecture from Thrace University, Terkida, Turkey (1991), a Master of Science in Thrace (Trakya) University, Edirne, Turkey (1994), and a PhD in Landscape Architecture, University of Ege Graduate School of Natural and Applied Sciences, Department of Landscape Architectures, Izmir, Turkey (1999).

In 2013, she was a visiting scholar at Michigan State University working with Dr. Jon Bryan Burley.