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Dependencies among Environmental Performance Indicators for Buildings and their Implications

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Abstract

Environmental performance rating schemes such as LEED allocate separate indicator scores for various criteria (or aspects). The overall environmental performance score is obtained by summing these separate scores. However, no mention is made regarding any dependencies among aspect indicators. In this study, possible influences, including their degree ('strong', 'moderate', and 'none') and direction (positive, negative) were identified among the seven aspects covering the sustainability of the building site (i.e. Site domain) in an environmental performance assessment scheme for buildings. These judgements were corroborated by the correlation coefficients corresponding to scores for those aspects achieved by 10 buildings. First and higher order influences were accounted for through a matrix-based scheme, which revealed aspects that were influencing others or being influenced by them. The degree of influencing other aspects was found to be inversely proportional to that of being influenced by them. The aspect weights, obtained by querying experts, appeared to be independent of their degree of influence. The negative dependencies in this Site domain gave rise to constraints on combinations of aspect scores and the maximum environmental performance score achievable. The score levels that would maximize this overall score were obtained through an optimization exercise; this generated some possible planning strategies.

Keywords: environmental performance indicators, indicator dependency, score correlation, degree of influence, constrained optimization, planning strategies

Highlights:

- High correlation between indicator scores may reflect indicator dependency
- Correlation coefficients are used to confirm the identified degrees of influence
- Direct and higher order influences are computed using matrix manipulations
- Negative dependencies constrain the achievable environmental performance score
- Results of constrained optimizations can be used to arrive at planning strategies

1. Introduction

The certification and rating of buildings as 'green' (i.e. having low environmental impacts) is gaining much importance today, with good reviews provided by Berardi [1] and Fowler and Rauch [2]. The best known scheme for such certification and rating is LEED (Leadership in Energy and Environmental Design), which originated in the US. This scheme can be seen as a Total Quality Assessment (TQA) system, where a building is assessed on many criteria; this can be contrasted with Life Cycle Assessment (LCA) systems, where only a few select indicators such as energy consumption and carbon emissions are assessed in a detailed quantitative manner over a building's entire lifecycle, from raw material extraction to demolition. In the LEED scheme the various criteria (each of which have varying possible maximum points) are grouped into six categories, namely sustainable site, water efficiency, energy and atmosphere, material and resources, indoor environment quality, and innovation and regional specificities. The BREEAM (Building Research Establishment Environmental Assessment Method) scheme, which originated in the UK, is essentially a similar approach. In these schemes, the points for all criteria are summed in order to obtain the overall score for environmental performance. The CASBEE rating system [1] however groups categories into two sets - namely building performance quality (covering the categories of indoor environment, quality of services and outdoor environment) and building environmental loads (covering the categories of energy, resources and materials, reuse and reusability, and off-site environment). The final score is based on the interaction between the two main groupings; a high score requires both high performance quality and low environmental loads.

Nevertheless, Berardi [1] and Fowler and Rauch [2] demonstrated considerable similarity across TQA schemes such as the above, and grouped the criteria in various TQA schemes into 5-6 categories, in order to compare their relative weights. Following their work, our own research [3] used the categories of Site, Energy efficiency, Water efficiency, Materials, Indoor environmental quality, and Waste and pollution in order to develop indicators for the environmental performance of buildings in Sri Lanka. We have however labeled the above categories as 'domains' of interest rather than 'categories' because the former is used in the wider sustainability indicator discourse [4, 5]. Furthermore, the criteria that make up a category have been called 'aspects' in our research – Table 1 gives our classification.

We have also defined non-dimensional ratio based indicators for all 33 aspects that characterize the six domains; computed values for those indicators from a set of 12 buildings; and presented various approaches for arriving at a total score for environmental performance [6]. Our approach can be considered an embodiment of a proposal by Cole [7], who argued that rating systems would be more consistent and comprehensible if all aspects had similar ranges for scores, with differences in the importance of aspects being dealt with by explicit weights. Our work above has contributed to the development of a recent green rating system [8]. Furthermore, we have also explored whether rating systems in fact deliver genuine environmental sustainability [6], because (i) they may not consider factors that are broader both geographically [9] and conceptually [10]; and (ii) they are essentially technological in nature, thus tending to increase consumption in various ways, rather than encouraging a return to simple lifestyles, reduced resource use and practices that encourage regeneration of resources [11].

We have proposed an approach similar to the LEED and BREEAM schemes, where indicator scores are summed to obtain the overall score [6]. Those schemes or their derivatives are the most widely used worldwide [12]. In this current paper however, we take a closer look at the indicator scores we computed and assess the degree of dependency among them. We use a correlation based approach, as well as one that logically assigns causal strength and direction from one indicator to another. We also study the implications of such dependency and show that they can help to fine tune planning strategies. The current rating schemes such as LEED or BREEAM say little or nothing explicitly about indicator dependency. It appears as if all the identified aspects (and corresponding indicators) are independent contributions to the overall sustainability score. We show that this is far from the case.

Cui and Blockley [13] defined four types of dependency, increasing in degree from "mutual exclusion" through "minimum dependence" and "independence" to "maximum dependence". They did this to model the effect of two or more precedents on an outcome. We do not attempt in this paper to define the degree of dependence with such granularity, but rather to capture the deviation from independence.

Alsulami and Mohamed [14] defined relevant indicators quantitatively, normalized them to the range (0,1) and then modified these using an adjacency matrix and fuzzy cognitive map [15] to capture the dependency among the indicators. Tseng [16] used techniques to classify

indicators as "autonomous", "independent", "linkage" and "dependent", based both on their dependence on other indicators (dependence power), and their ability to influence other indicators (driving power). Lin et al [17] calculated the degree (D) of direct or indirect impact of a criterion on other criteria, and also the degree (R) to which a criterion is impacted by other criteria. The strength of relation among criteria was defined by (D+R), while that of causality by (D-R).

Wagenhals et al. [18] obtained the indicator weights by pair-wise comparison of indicators, following the basic approach of Krajnc & Glavic [19]. They then defined the dependency of a given indicator on another (and vice versa) using a 5 level scale, namely "very strong", "strong", "medium", "weak" and "very weak"; and also the direction of dependence, i.e. whether positive or negative. This led to 11 labels for dependency, including "none". They then used the dependence to modify the weighted indicator scores when calculating the overall sustainability index.

Many of the above authors have used fuzzy techniques to convert linguistic labels to numbers that can be used in computations. Dependence among indicators has also been studied in relation to country risk indicators [20] and credit risk [21]. However, the literature on indicator dependency is sparse compared to that covering the straightforward aggregation of indicator scores to arrive at an overall score or index. Hence, our research on indicator dependency can be seen as a contribution to a literature sparse research field.

As will be seen below, our work covers aspects such as indicator influence matrices; levels of dependency and/or influence; computation of the degrees of influence and being influenced; and relationships between weights and influence strengths, all of which are covered to some degree in the literature referred to above. We argue however that our work is novel in applying these ideas to rating systems such as LEED, about which no dependency related literature could be found. More genuine novelty can be claimed for demonstrating how negative dependencies generate constraints that limit the maximum possible overall environmental performance score; furthermore we show how the above constrained maxima can be achieved by appropriate trade-offs between indicators that can be made at the planning stage.

2. Objectives and Rationalé

The objectives and scope of the research reported in this paper, together with the rationale' for the same, are as follows:

- 1. To study the dependencies among indicators, using those in the Site and Energy efficiency domains as examples. The Site and Energy efficiency domains are the most strongly weighted domains in most rating systems; they account for 48% of the weights in the system proposed for Sri Lanka, with the Site domain accounting for 26% [3]. Hence, we concentrate on the Site domain aspects since the domain has the greatest weight; also, the negative dependencies found there generate some interesting implications. More detail about the Energy efficiency domain can be found elsewhere [22], although some results are reported here. We focus on intra-domain indicator dependencies, since inter-domain ones are likely to be less significant [22].
- 2. To consider two major implications of the above dependency, namely (i) the relationship between the indicator weights and their dependencies; and (ii) the constraints for probable indicator scores that can be achieved concurrently in a given project or building when there are negative dependencies among indicators.
- 3. To present a methodology for the constrained optimization of the overall environmental performance score, in this case only for the Site domain, which has many negative dependencies; also to demonstrate how the results can be used for very practical planning decisions.

3. Dependencies among Indicators

As described in our previous work [6], indicators for all 33 aspects (listed in Table 1) were obtained from buildings that had sought certification on the basis of a recently introduced Sri Lankan rating scheme [8]. Only 12 buildings were available for scoring because of the relatively new scheme; but this limitation can be tolerated somewhat because of the reasonably low standard deviations of the scores [6]. Note that only the first 10 buildings were used for the correlation, since certification had not been sought for the last two; they

were used for comparison in a previous paper [6]. Table 2 gives seven defining characteristics with respect to the siting of these buildings, all of which were located in urban Sri Lankan settings. These are the ratio of un-built to total site area; number of services within 0.8 km of the site; number of bus stands for 2 bus lines within 0.4 km of the site; population within 0.4 ha centred on the site; number of residential or commercial or other units within the above 0.4 ha; ratio between vegetated and total area; and ratio between shaded and total hardscape. It is the characteristics in Table 2 that are used to generate each of the seven indicator scores in Table 3, after being linearly normalized by their benchmarks [6].

Table 4 gives the matrix of correlation coefficients (for which an upper triangular matrix is sufficient). Correlation coefficients in excess of 0.7 (whether positive or negative) are indicated in bold, signifying both "very strong" (over 0.9) and "strong" (0.7 to 0.9) correlations; whereas those between 0.5 and 0.7 are underlined, signifying "moderate" correlation [23].

We now explore why there could be such correlation by positing plausible causal influences between each of the aspects. We signify whether the influence is direct or inverse by using positive or negative signs respectively. Furthermore, we use an integer scale from zero to two to indicate the strength of the influence as 'none' (0), 'moderate' (1) and 'strong' (2) – see the list below, which also includes in parentheses the corresponding correlation coefficients from Table 4. The matrix representing such influences for the Site domain is presented in Table 5; and the assigned values explained below – note that we need a full matrix to represent influences, since they need not be reciprocal (unlike correlations).

- 1. Land use \rightarrow Housing density (-1): When un-built area increases the number of units that can be housed will reduce (r = -0.47)
- Land use → Landscape design (+2): When un-built area increases there is more space available for landscaping (r = +0.91)
- Land use → Microclimate (+1): When there is more un-built area there will probably be less hardscape (r = + 0.59)
- 4. Infrastructure efficiency \rightarrow Transportation (-1): When there are a number of services available around the development, less transportation is required (r = +0.26)

- 5. Infrastructure efficiency \rightarrow Housing density (+1): When the number of basic services in the area increases there is more demand for housing of units (r = +0.62)
- Transportation → Infrastructure efficiency (-1): When good transportation is available people will travel large distances for basic services (r = +0.26)
- 7. Transportation \rightarrow Housing density (+1): When transportation facilities increase there will be more demand for housing of units, and an increase in the density (r = +0.62)
- Site selection → Infrastructure efficiency (+1): When a dense site is selected it would have good services (r = +0.36)
- 9. Site selection \rightarrow Transportation (+1): It is more likely that there will be good transportation facilities for previously developed sites (r = +0.27)
- 10. Site selection \rightarrow Housing density (+2): Previously developed sites will have an increased housing density (r = +0.72)
- 11. Housing density \rightarrow Land use (-2): When housing density increases the total foot print of the built area will increase, and the un-built area will decrease (r = -0.47)
- 12. Housing density \rightarrow Infrastructure efficiency (+1): When housing density increases there is more demand for infrastructure (r = +0.62)
- 13. Housing density \rightarrow Transportation (+1): When housing density is high there will be good transportation (r = +0.62)
- 14. Housing density \rightarrow Landscape design (-1): When housing density is high landscaped area will be reduced (r = -0.62)
- 15. Landscape design → Land use (+1): When a greater area is used for landscaping the un-built area also increases (r = + 0.91)
- 16. Landscape design → Microclimate (+1): Good landscaping can increase shading and reduce heat island effects (r = +0.56)

[Note that the term 'housing' is used in the sense of 'accommodating']

In this way, there were 16 plausible influences that were identified (out of the 42 possible relationships). The correlation coefficients served as a guide to corroborate the posited influences, including their directions and strengths. So for example, influences 2 and 10 above have strengths of +2 and r values of +0.91 and +0.72 respectively. Similarly influences 5 and 7 both have strengths of +1 and r values of +0.62. The corroboration is far from perfect however. Influence 11 has a strength of -2 but an r value of only -0.47; while influence 15 has a strength of only +1 but an r value as high as +0.91. Furthermore, influences 4 and 6 have strengths and r values of differing sign. Nevertheless, the overall corroboration of the

influence strengths by the r values can be deemed as reasonably good. Note that Alsulami and Mohamed [14] and Wagenhals et al. [18] have also tried to capture influences between indicators using linguistic labels converted to numeric values. The corroboration of such qualitative judgements via correlation coefficients as we have done is however novel, to our knowledge.

4. Higher order Dependencies

The first order influences can be represented in matrix form, and Table 6 shows such a matrix that has been normalized after dividing by the highest row sum. The row sums represent the degrees to which each aspect indicator influences others; while the column sums represent the degree to which they are susceptible to being influenced.

We now follow the work of Boulanger [24], who has used a modified matrix adjacency approach for ecological modeling, capturing both first and higher order influences between entities. Consider Figure 1, where P, Q and R represent physical entities in an ecosystem for Boulanger [24], but aspects of a rating system for us. The figure depicts both direct (e.g. $P \rightarrow Q$ and $P \rightarrow R$) and indirect (i.e. double link, e.g. $P \rightarrow R \rightarrow Q$) influences for a 3 aspect system. In addition to the indirect influences depicted, 'cyclic' influences are also possible and described below, though omitted from Figure 1 for clarity.

We can use a matrix of influences such as in Table 7(a), calling it matrix [A], to represent some (arbitrarily chosen) direct influences. As seen in Table 6, a matrix of influences need not be symmetrical, unlike a matrix of correlations. The matrix [A] indicates that the (direct) influence of P on Q ($P \rightarrow Q$) = +0.5; that of P on R ($P \rightarrow R$) = +0.25; and that of R on Q ($R \rightarrow Q$) = -0.25. Note that the principal diagonal has zeros because there is no direct influence of an aspect on itself.

It is intuitive that the second order influence (or 'first level' indirect influence) of P on Q $(P \rightarrow R \rightarrow Q)$ will be the product of the direct influences of P on R and R on Q, i.e. (+0.25) x (-0.25) = -0.063. It can be shown that the matrix of these 'first level' indirect influences is obtained by multiplying the matrix [A] by itself to obtain [A]². The matrix [A]² is shown in Table 7(b); it indicates that the (second order) influence of P on Q is indeed -0.063. The other

thing to note is that the principal diagonals are now non-zero. This is because of 'cyclic' indirect influences. So the first level indirect influence of P on P will be obtained as $(P \rightarrow Q \rightarrow P)$ plus $(P \rightarrow R \rightarrow P) = (P \rightarrow Q)(Q \rightarrow P) + (P \rightarrow R)(R \rightarrow P) = (+0.5)(+0.25) + (+0.25)(-0.25) = +0.063$, which is given in the first cell of matrix [A]² in Table 7(b).

We can see that the numbers depicting influences are smaller in Table 7(b) than in Table 7(a). Similarly, higher order influences will be smaller still; and if the total influence is represented by the matrix $[A]^* = [A] + [A]^2 + [A]^3 + \dots + [A]^n$, the members of $[A]^*$ will converge fairly soon. This type of recursive convergence has been proposed by Alsulami and Mohamed [14] too; however, the method we propose is much simpler and easily computed.

Table 8 gives the final table of influences, or [A]^{*}, for the aspects in the Site domain. If we compare the matrix [A]^{*} (Table 8) with the matrix [A] (Table 6), we see that the aspect which most highly influences others has changed from site selection to land use; while housing density has remained as the one being most influenced by others. The general trend however remains more or less the same – see Figure 2, which plots the relationship between the direct and total influences, but only for non-zero direct influences. The slope of the regression (1.55) indicates that the total influences are approximately 50% higher than the direct ones. The line also passes very close to the origin and the coefficient of determination is fairly high; this means that the relative magnitudes and directions of the direct influences have not changed very much. As described above, however, there could be some significant individual variations. These dependencies and their higher order effects therefore appear to be of some importance. What is less clear is what this implies and how it should be used, both in decision making and in the defining of rating system aspects and even their weights. We consider these questions below.

5. Implications of Dependency

Given that we have indices for the degree of influencing other aspects/indicators (row sums in Table 8) and also the degree of being influenced by others (column sums in Table 8), we can now check the relationship if any between the two for the Site domain. This is presented in Figure 3, which portrays a strong negative correlation between the two entities; note that the figure gives an R^2 value (i.e. the coefficient of determination) of 0.99. This implies that if

an aspect tends to causally influence other aspects, it is unlikely to itself be influenced much by those indicators. Although notions regarding degrees of influencing and being influenced have been presented by Lin et al. [17] and Tseng [16], the insight regarding this inverse relationship is novel. A similar negative correlation was obtained for the Energy efficiency domain, with an R^2 value of 0.82.

The question also arises as to the relationship between the weights obtained for these aspects [3] and the degrees to which they influence or are influenced by other aspects. If say an aspect strongly influences other aspects (as discovered above), should that be reflected in its weight or should the weight merely reflect the aspect's impact on the environment? On the other hand, even though an aspect is strongly influenced by other aspects (with little or no influence on those others), can its weight still not be high, because its own environmental impact is high? This research only begins to answer such questions, but they are well worth pursuing in further studies.

What we have done here is to take the aspect weights [3] and the degrees of influence (row sums in Table 8) and check whether there is any correlation. The resulting R^2 value obtained for the Site domain is 0.02; while that for the Energy efficiency domain is 0.003 (Figures 4(a) and (b)). This limited exploration appears to indicate that the aspect weights, obtained from expert surveys [3], do not primarily reflect their influence on or by other aspects, but rather their own environmental impact. In other words, we could tentatively say that aspects weights are independent of their influence on other aspects. Once again we emphasize that more research is required on this entire issue of aspect dependency.

It is not clear whether the developers of rating systems ignored these dependencies or in fact deliberately allowed them. If, as our tentative findings above suggest, the aspect weights are independent of the of their degrees of influence, then perhaps one way of accounting for these degrees of influence would be to deliberately build in dependent aspects. For example, in the exercise carried out for the Energy efficiency domain [22], the greenhouse gas emission indicator was highly (and positively) influenced by all the other indicators – i.e. by energy usage, building envelope performance, lighting efficiency and renewable energy percentage – while not itself influencing any other indicator. So, although the greenhouse gas emission indicator can be completely 'explained' by the other indicators (and hence arguably left out), the fact that it is separately accounted for can be considered a measure of the degrees of

influence of those other indicators. At the same time, having too many dependent aspects in a rating system could be tantamount to 'double counting'. Such findings will hopefully encourage future research into conceptual as well as practical aspects of indicator dependency in the context of rating systems.

We now consider another implication of indicator dependency, in particular of negative dependency. The Site domain has many such negative dependencies between aspects, although the Energy efficiency domain has only positive dependencies [22]. If there are negative dependencies between two aspects, it would then follow that indicators for both those aspects are unlikely to be at their maximum possible values. This has implications for the optimization of overall environmental performance scores, as we shall see in the next section. As a prelude to that, we explore the constraints that are likely to characterize such optimization.

Let us consider that any aspect indicator can assume one of three levels, namely low, medium or high. If there is a 'moderate' negative influence of one aspect on another in any direction (see Table 5 for cells with -1), we could posit that both indicators cannot be at a high level simultaneously; in other words, if one indicator is at a high level, the other cannot be at a level greater than medium. This constraint is illustrated in Figure 5(a) for the aspects infrastructure efficiency and transportation. If however there is a 'strong' negative influence of one aspect on another in any direction (see Table 5 for cells with -2), we could say by extension that if one indicator is at a high or medium level, the other cannot be at a level any greater than low. This constraint is illustrated in Figure 5(b) for the aspects land use and housing density. The above constraints are utilized in the optimization exercise that follows.

6. Optimization of Environmental Performance Scores

The question of optimization arises because of the negative dependencies discovered among indicator scores (e.g. in the Site domain). We have already seen the constraints spelt out in Figures 5(a) and 5(b), where aspect indicator scores are assumed to have discrete levels corresponding to high, medium and low. The numeric indicator scores (normalized with respect to their benchmarks) corresponding to these levels for the Site domain aspects are taken as the maximum, average and minimum values in Table 3. The objective of the

exercise was to find the combinations of indicator score levels that would result in a maximum or near maximum overall environmental performance score for the Site domain.

The details of the optimization are found elsewhere [22]. It involves binary coding so that genetic algorithm type approaches could be employed for a larger number of combinations. For the present exercise, even an exhaustive search of the 343 possible combinations would suffice. The results are presented in Table 9 for the combinations that yield the top 4 overall scores, together with those scores.

The highest score achieved is 39.3. If there are no constraints, then all the levels would have been at high, and the overall score would have been 52.7. This shows that the constraints due to the presence of negative influences prevent the maximum overall score being reached. It should also be noted that the maximum weight for the Site domain is 25.7 (expressed as a percentage) [3]. The question arises then as to how the maximum possible (i.e. constraint free) maximum score can reach 52.7. This is because we are using 'continuous score functions' as opposed to step functions [6]. The former approach rewards above-benchmark performance and will allow the overall performance score for the Site domain to exceed 25.7, which would be achieved for a building where all aspects on average are at their global benchmark values.

It can be observed that the highest overall score is achieved by keeping the housing density score low, thus allowing both the land use and landscape design ones to be high. This score is higher than having the housing density score high; because then the land use one will need to be low (strong negative influence constraint) and the landscape design one average (moderate negative influence constraint). When translated to a planning decision, this would suggest that preserving greater un-built areas in a site would contribute to a higher environmental performance score than creating greater housing density. Similarly, having the transportation indicator high and the infrastructure efficiency one average is better than their being vice versa (moderate negative influence constraint). When translated to a planning decision, this would suggest that providing or seeking better transportation linkages would contribute to a higher environmental performance score than seeking or creating mixed development in a site. It should be noted that these conclusions are dependent not only on relative weights, but also on the relative (normalized) ranges of scores achievable.

The above planning strategies may not necessarily mean that lower environmental impacts are in fact being achieved thereby. That depends on how well the rating scheme being used genuinely reflects environmental performance, and doubts about that have been raised in the introduction to this paper and elsewhere [6, 9-11]. In addition, there is also the question about how accurate the assessments are. However, given a particular rating system, if a building owner, developer or manager wants to maximize its performance score, the above approach to trade-offs can be used in the presence of negative dependencies. Seeking to increase the scores for highly weighted aspects is of course another obvious way of maximizing the environmental performance score.

The above implications of negative dependencies for planning strategies are a very practical way in which this research can influence practice. While it is not clear whether these implications were envisaged or not by rating system developers, scoring systems of all types will not only reward performance but also induce behavior that could primarily be reward-seeking as opposed to performance-improving. This research has highlighted the implications of negative dependencies. While those using rating systems may want to exploit the possibilities raised here, those developing rating systems should judge whether such exploitation is to be encouraged, tolerated or discouraged.

7. Conclusions

- It was possible to identify strengths and directions of influences between aspects within the Site and Energy efficiency domains, using the correlation coefficients as a guide. For example, in the Site domain, there is a very strong positive influence of land use on landscape design and a very strong negative influence of housing density on land use.
- A matrix multiplication cum summation approach was used to represent and quantify the direct and indirect influences between aspects. In the Site domain, the aspect that most influences others was found to land use; while housing density was the aspect most influenced by others.
- 3. The degrees of influencing and being influenced for aspects in both the Site and Energy domains were inversely correlated with high coefficients of determination.
- 4. Low or negligible coefficients of determination between aspect weights and their degrees of influencing other aspects suggest that the weights reflect their actual environmental

impacts much more than their influence on other aspects. This means that aspects weights supplied by experts appear to be independent of the influence of one aspect on another.

- 5. Constraints to achieving the maximum possible environmental performance score derive from negative dependencies between indicator scores; these dependencies can be classified as strongly or moderately negative.
- 6. Strongly negative dependencies create a greater number of unlikely indicator level combinations. These subsume the unlikely indicator level combinations generated by moderately negative dependencies.
- 7. Studying the implications of constraints for environmental performance scores can help us to arrive at planning decisions. For example, given the rating system and context we have described, preserving greater un-built areas in a site (land use) and improving landscape design would contribute to a higher environmental performance score for the Site domain than creating greater housing density. Similarly, providing or seeking better transportation linkages would contribute to a higher environmental performance score than creating mixed development in a site (infrastructure efficiency). Such planning strategies are dependent not only on relative weights, but also on the ranges of relative (normalized) scores that are achievable.

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Domain	Aspects
Site	Land use
	Site selection
	Infrastructure efficiency
	Transportation
	Housing density
	Microclimate
	Landscape design
Energy	Energy usage
Efficiency	Building envelope performance
	Lighting efficiency
	Greenhouse gas emission
	Renewable energy
Water Efficiency	Water conservation
	Water efficient landscaping
	Sustainable water technologies
Materials	Local/regional materials
	Renewable material
	Recycle material
	Reuse material
	Embedded energy
	Carbon content
	Durability
Indoor	Occupant health & safety
Environmental	Thermal comfort
Quality	Daylight
	Acoustic & noise control
	Visual quality
	Indoor air quality
Waste &	Waste reduction
Pollution	Waste management strategies
	Waste water management
	Operational waste
	Flexible building plan
X	

Table 1 - Domains and aspects for environmental performance of buildings (from [3])

	Un-built/	Services	Bus stands (for 2	People/	Units/	Vegetated/	Shaded/total
	total area	in 0.8 km	lines) in 0.4 km	0.4 ha	0.4 ha	total area	hardscape
Building 1	0.215	13	3.0	1800	25	0.050	0.41
Building 2	0.645	3	0.5	1350	4	0.378	0.65
Building 3	0.188	15	1.4	2100	28	0.120	0.45
Building 4	0.200	8	1.2	1650	10	0.140	0.50
Building 5	0.100	7	1.2	2100	20	0.040	0.25
Building 6	0.088	8	1.4	1950	15	0.030	0.30
Building 7	0.088	20	1.0	1800	18	0.024	0.60
Building 8	0.180	14	1.2	2250	18	0.090	0.40
Building 9	0.113	12	1.0	1350	12	0.164	0.36
Building 10	0.135	9	1.3	1650	10	0.086	0.50

1650

0.50

Table 2 – Characteristics of the 10 buildings used for the survey and analysis

Building 10

0.135

Table 3 – Scores for the aspects in the Site domain obtained by the sample of 10 buildings

1.3

	Land	Infra-	Transport-	Site	Housing	Landscape	Micro-
	use	structure	ation	selection	density	design	climate
Building 1	0.86	1.30	3.00	1.20	2.50	0.25	0.81
Building 2	2.58	0.30	0.50	0.90	0.40	1.89	1.30
Building 3	0.75	1.50	1.40	1.40	2.80	0.60	0.90
Building 4	0.80	0.80	1.20	1.10	1.00	0.70	1.00
Building 5	0.40	0.70	1.20	1.40	2.00	0.20	0.50
Building 6	0.35	0.80	1.40	1.30	1.50	0.15	0.60
Building 7	0.30	2.00	1.00	1.20	1.80	0.12	1.20
Building 8	0.72	1.40	1.20	1.50	1.80	0.45	0.80
Building 9	0.45	1.20	1.00	0.90	1.20	0.82	0.72
Building 10	0.54	0.90	1.30	1.10	0.95	0.43	1.00
Minimum	0.30	0.30	0.50	0.90	0.40	0.12	0.50
Average	0.78	1.09	1.32	1.20	1.60	0.56	0.88
Maximum	2.58	2.00	3.00	1.50	2.80	1.89	1.30

	Land use	Infra- structure	Transport- ation	Site selection	Housing density	Landscape design	Micro- climate
Land use	1.00	<u>-0.55</u>	-0.28	-0.46	-0.47	0.91	<u>0.59</u>
Infra- structure		1.00	0.26	0.36	<u>0.62</u>	<u>-0.55</u>	0.07
Transport- ation			1.00	0.27	<u>0.62</u>	<u>-0.51</u>	-0.34
Site selection				1.00	0.72	<u>-0.64</u>	-0.49
Housing density					1.00	<u>-0.62</u>	-0.42
Landscape design						1.00	<u>0.56</u>
Micro- climate							1.00

Table 4 – Correlation coefficients (r) for aspect scores from the 10 buildings

Table 5 Influence metrix fo	r aspects in site domain
Table $J = $ influence matrix to	r aspects in site domain

	Land use	Infra- structure	Transport- ation	Site selection	Housing density	Landscape design	Micro- climate
Land use					-1	2	1
Infra- structure			-1		1		
Transport- ation	Ć	-1			1		
Site selection		1	1		2		
Housing density	-2	1	1			-1	
Landscape design	1						1
Micro- climate							

	Land use	Infra- structure	Transport- ation	Site selection	Housing density	Landscape design	Micro- climate	Degree of influencing
Land use	0	0	0	0	-0.25	0.50	0.25	0.50
Infra- structure	0	0	-0.25	0	0.25	0	0	0.00
Transport- ation	0	-0.25	0	0	0.25	0	0	0.00
Site selection	0	0.25	0.25	0	0.50	0	0	1.00
Housing density	-0.50	0.25	0.25	0	0	-0.25	0	-0.25
Landscape design	0.25	0	0	0	0	0	0.25	0.50
Micro- climate	0	0	0	0	0	0	0	0.00
Degree influenced	-0.25	0.25	0.25	0.00	0.75	0.25	0.50	

Table 6 – Degrees of influencing and being influenced: first level of influence

Table 7 - (a) First and (b) second level influences for interacting entities in Figure 1

7(a) – Matrix [A]	Р	Q	R
Р	0	+0.5	+0.25
Q	+0.25	0	-0.5
R	-0.25	-0.25	0
$7(b) - Matrix [A]^2$	Р	Q	R
Р	0.063	-0.063	-0.250
Q	0.125	0.250	0.063
R	-0.063	-0.125	0.063

	Land use	Infra- structure	Transport- ation	Site selection	Housing density	Landscape design	Micro- climate	Degree of influencing
Land use	0.39	-0.08	-0.08	0.00	-0.38	0.78	0.54	1.17
Infra- structure	-0.17	0.12	-0.21	0.00	0.27	-0.15	-0.08	-0.23
Transport- ation	-0.17	-0.21	0.12	0.00	0.27	-0.15	-0.08	-0.23
Site selection	-0.51	0.36	0.36	0.00	0.80	-0.45	-0.24	0.33
Housing density	-0.86	0.27	0.27	0.00	0.35	-0.76	-0.40	-1.14
Landscape design	0.34	-0.02	-0.02	0.00	-0.10	0.20	0.38	0.79
Micro- climate	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Degree influenced	-0.98	0.44	0.44	0.00	1.21	-0.54	0.13	

Table 8 – Degrees of	of influencing	and	being	influenced:	sum	of	all	first	and	higher	order
influences											

Table 9 – Combinations of aspect indicator levels yielding high overall scores for the Site domain

Land	Infra-	Transport-	Site	Housing	Landscape	Micro-	Overall
use	structure	ation	selection	density	design	climate	Score
High	Average	High	High	Low	High	High	39.3
Low	Average	High	High	High	Average	High	38.8
High	High	Average	High	Low	High	High	37.6
Low	High	Average	High	High	Average	High	37.1

FIGURE CAPTIONS

- Figure 1 First order (direct) and second order (indirect) influences among three entities
- Figure 2 Relationship between non-zero direct influences and their final total influences
- Figure 3 Degree of influencing vs being influenced for aspects in the Site domain
- Figure 4 (a) Relationship between degree of influencing and weight for aspects in the Site domain
- Figure 4 (b) Relationship between degree of influencing and weight for aspects in the Energy efficiency domain
- Figure 5 Possible indicator score level combinations for (a) housing density and land use aspects and (b) transportation and infrastructure efficiency. Note that dark shading defines combinations that are not allowed.



Figure 1 – First order (direct) and second order (indirect) influences among three entities



Figure 2 – Relationship between non-zero direct influences and their final total influences



Figure 3 – Degree of influencing vs being influenced for aspects in the Site domain



Figure 4 (a) – Relationship between degree of influencing and weight for aspects in the Site domain



Figure 4 (b) – Relationship between degree of influencing and weight for aspects in the Energy efficiency domain



Figure 5 – Possible indicator score level combinations for (a) transportation and infrastructure efficiency and (b) housing density and land use aspects. Note that dark shading defines combinations that are not allowed.