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A framework for guiding the management of urban stream health

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ABSTRACT

Urban stream ecosystems are vulnerable to urbanisation of surrounding land cover and land use. We study 30 sites along two highly urbanised streams in Brisbane, Australia. Fieldwork generated a suite of primary stream health indicators. Geographic information system techniques generated spatially-explicit metrics of land cover and a lumped metric of nearby population that put stress on stream health. Stream health indicators were aggregated into a stream health index, and land-use stress indicators were aggregated into a land-use stress index, using data envelopment analysis (DEA). DEA was then applied to these indices to create an ecological performance index. Dominator analysis generated a set of practical role models for each ecologically underperforming site. A subsequent round of DEA was applied to the stream health index and multiple stress indicators to calculate response elasticities of stream health with respect to specific stress indicators. Empirical findings show widespread deviations beneath best practice, enlightening dominator relationships, and informative variation in response elasticities. Each of these findings can provide guidance to those responsible for allocating scarce resources in an effort to improve the health of Brisbane's urban streams.

1. Introduction

Local catchment groups and governments invest time and money protecting and rehabilitating urban streams, their riparian zones and catchments. It is therefore important from the outset to identify which areas will be most responsive to these efforts so that scarce resources can be allocated for maximum benefit. In this paper we develop an analytical framework that incorporates measures of both urban stream health and land-use stress. The framework begins with fieldwork, continues with geographic information system (GIS) techniques, and concludes with data envelopment analysis (DEA) and dominator analysis. DEA and dominator analysis identify sites most in need of attention and dominating role models for them. DEA also creates endogenous weights for use in constructing health and stress indices and calculating response elasticities of stream health with respect to changes in alternative land-use stress measures. We provide an empirical application to 30 highly urbanised stream sites within the Bulimba Creek and Norman Creek (BCNC) sub-catchments of the Brisbane River, Australia, to illustrate how the framework achieves these objectives. This ecological performance analysis is the first application of DEA to urban stream ecology.

1.1. Addressing Stream Health and Stream Stress Factors

Due to the complex nature of urban stream ecosystem processes, the mechanisms by which land cover and hydrological alteration impact urban stream health have not been directly demonstrated, although correlations have been established. A range of stressors have been shown to influence the health of urban streams, including altered hydrology and channel morphology, habitat fragmentation and loss, high nutrient levels, pollutants, and invasive species of plants and animals, and have been collectively referred to as the “urban stream syndrome” (Meyer et al., 2005; Walsh et al., 2005b). However at different spatial scales and in different locations the relative importance of these urban stream stressors varies. For example, in-stream connectivity was found to be important to fish assemblage, pollution levels and habitat quality in Puerto Rico (Ramírez et al., 2012), hydrological alteration associated with levels of catchment-scale impervious surface was found to be the most important land-cover feature impacting macroinvertebrate and fish community structure in Victoria, Australia (Walsh et al., 2005a) and in Georgia, USA (Roy, 2004), and intact riparian tree cover at the reach scale was found to have a detectable benefit on macroinvertebrate community structure in Victoria (Thompson and Parkinson, 2011).

Failure to apply stream health management intervention at a scale appropriate to capture the driving processes has been blamed for the poor performance of many rehabilitation activities. The most common approach to planning and prioritising stream rehabilitation projects is based on ‘available land opportunities’, with the result that most stream

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rehabilitation activities are undertaken in headwaters and small tributaries, although the habitat and land-use changes which are most severe are commonly in lowland floodplains and deltas (Bernhardt et al., 2005; Hermoso et al., 2012).

Inspired by the systematic conservation planning used for reserve design (Ardron et al., 2010; Margules and Pressey, 2000), a systematic "efficient planning" approach for river rehabilitation that focuses on ecosystem processes at the whole-catchment scale has been proposed (Hermoso et al., 2012). This approach allows for the efficient selection of areas for rehabilitation based on socio-economic constraints and facilitates decision-making by integrating and prioritising the trade-offs among multiple rehabilitation actions using multiple-objective optimisation (Czyzak and Jaszkiewicz, 1998).

Proponents of systematic planning have not yet articulated a practical framework of how such an approach would be applied to stream rehabilitation. Ideally their framework would allow easier integration and comparison of alternative rehabilitation actions for managers to consider and would address the driving ecosystem processes. The aim of the present study is to further elucidate options for protection and rehabilitation of freshwater urban ecosystems as well as the scale of mitigation efforts that might be required.

1.2. The Southeast Queensland Approach

Healthy Waterways is a not-for-profit, non-government organisation devoted to the protection and improvement of waterways in southeast Queensland (SEQ). It operates an Ecosystem Health Monitoring Program (EHMP) that reveals whether the health of regional waterways is improving or deteriorating. It uses a broad range of biological, physical and chemical indicators of ecosystem health, including fish and invertebrate biodiversity metrics, ecosystem process metrics and water quality metrics.

The EHMP was fully implemented in 2002/03. 135 freshwater stream sites, rural and urban, in SEQ are sampled biannually (spring and autumn), their health indicators are measured, and report cards are made public in annual reports. The overall health of a site is measured relative to an agreed reference condition (Bunn et al., 2010). Many local councils use the results of the EHMP as a guide to how well they are protecting their streams.

The general poor health of urban streams in the Lower Brisbane Catchment is well documented. In the 2013 EHMP report, the Lower Brisbane Catchment, which includes the BCNC sub-catchments, received a grade of D-, down from a grade of D+ in 2012 but up from a grade of F in the previous six years (www.healthywaterways.org). Grades are based exclusively on stream health indicators, and although EHMP health indicators help identify the most likely stressors, and EHMP acknowledges "significant signs of stress," particularly at urban sites, EHMP does not consider stressors in the calculation of report card grades.

Effective management of urban stream health requires an understanding of the interrelationships among health indicators, among stressors, and between the two. Achieving such an understanding requires an analytical framework that incorporates both health and stress indicators. We introduce such a framework below.

1.3. Evaluating the Relative Performance of Stream Sites

We use fieldwork to generate stream health indicators, and GIS techniques to generate stress indicators, at stream sites. We apply DEA to the two sets of indicators to generate a health index and a stress index. A best-practice ecological performance frontier created from these indices is used to benchmark the performance of each site against best practice. We augment DEA with dominator analysis to identify for each site a set of role model sites that exhibit superior ecological performance. Dominators are not necessarily ecologically efficient, but they are healthier than dominated sites that have equal or less stress. An investigation of dominators can lead to the discovery of important factors not included in the DEA models.[1]

DEA is particularly useful when comparing like with like, and sites in the BCNC sub-catchments have relatively homogeneous environmental features (climate, topography, soils, geology and natural vegetation), and being contained in the Lower Brisbane Catchment, they can all be classed as degraded.

As a performance evaluation tool DEA has four noteworthy virtues: (1) it accounts for *both* stream health *and* stress factors when evaluating sites; (2) it combines *multiple* health indicators and *multiple* stress indicators that are measured in their own units; (3) its evaluation of each site is *relative* to the performance of all other sites in the sample, rather than to an agreed reference condition used by EHMP; and (4) being a linear programme, DEA has both primal and dual formulations, and the dual formulation creates endogenous weights for index construction and for the calculation of elasticities of stream health with respect to specific stress indicators at each site. Thus, while BCNC may well be in generally poor health, a DEA can distinguish degrees of poor health at the sampled sites, and it can relate degrees of poor health to specific stress indicators at sampled sites.[2] The endogenously determined weight profile of a site reveals its relative ecological strengths and weaknesses, and provides clues to the underlying processes.

DEA and dominator analysis can complement systematic planning by assisting in both adaptive management of rehabilitation projects already implemented (Wenger et al., 2009), and proactive management to identify which catchments and sites are priorities for future rehabilitation (Hermoso et al., 2012).

The paper unfolds as follows. In Sections 2 and 3 we explain how we have created our data set. In Section 4 we contrast index construction using exogenous and endogenous weights. In Section 5 we present DEA and dominator analyses, which construct health, stress and performance indices, calculate response elasticities, and identify role models for each site. Section 6 contains our empirical findings and discussion, and Section 7 concludes.

2. Data Collection

Data used in this study were generated by fieldwork and GIS techniques.

2.1. Fieldwork

Brisbane, the state capital located on the Lower Brisbane River, is the major population centre in SEQ, with approximately 2 million people in the greater Brisbane area and 3 million in the region. Population growth continues to be one of the key threats to the sustainability of stream health in SEQ.

Stream health data (macroinvertebrate and water quality) were collected for 30 sites in the BCNC sub-catchments of the Lower Brisbane River, during the post-wet season in April 2010. Sites were selected to include a range of levels of total sub-catchment impervious land cover and associated stormwater drains and piping, as well as a range of tree, grass and impervious riparian land cover at the reach and catchment scales. Another objective of site selection was to include nested sites and longitudinally connected sites that covered an extensive

[1] Cooper et al. (2000) provide a comprehensive survey of DEA and its uses, and Tulkens (2006) does the same for dominator analysis.

[2] A reviewer notes that much stream condition-stressor analysis is based on residuals generated by multiple regression analysis, and asks how different this is from distances from a DEA best practice frontier. The motivations are similar, but DEA offers three advantages: (a) its *best-practice* standard is more appealing than an *average-practice* standard; (b) it requires no pre-specified functional form, and so allows the data to determine the standard, whereas a regression-based standard is conditional on the functional form of the regression equation; and (c) it accommodates multiple outputs and multiple inputs naturally, and so is not constrained to specify a single dependent variable, as regression analysis is. The latter two advantages also apply to stochastic frontier regression analysis.

component of the BCNC sub-catchments. Sites that were completely piped underground could not be included for obvious access reasons.

Only health indicators reflecting in-stream, riparian and catchment processes which might indicate differences due to stressors at different scales were considered. Macroinvertebrate indicators have been associated with reach- and catchment-scale riparian condition as well as broader catchment processes, dissolved oxygen and temperature have been more strongly associated with reach- and catchment-scale riparian condition than broader catchment processes, while pH and conductivity have been associated most strongly with broader catchment processes (Bunn et al., 2010; Walsh et al., 2005b).

2.2. GIS

GIS techniques were used to determine population density and land-cover metrics for different land-cover configurations. In highly urbanised catchments such as those in BCNC, many streams are piped underground or flow under roads and are thus not simply connected on the surface. Hence, to create a connected stream network that incorporates both surface and piped flow, it was necessary to construct an artificial surface stream network by treating the piped flow as surface flow.[3]

Our study aims to investigate the role of the riparian zone in urban stream health by investigating spatial impacts of tree and total (tree and grass) vegetation cover, impervious surface and stormwater piping. We consider three spatial scales: (1) *reach scale* is the area 30 m either side of the stream to a distance of 200 m upstream of a site; (2) *local scale* is the area within several hundred metres in all directions upslope of a site; and (3) *catchment scale* is the total drainage area upstream of a site. Fig. 1 illustrates the spatial scales and land-cover configurations we use. They range from non-spatial or lumped metrics to spatially-explicit metrics such as inverse distance-weighted (IDW) metrics and areal buffer metrics.

3. Data Pre-processing

A sample of 30 sites imposes a degrees of freedom constraint, which in turn requires a minimally informative variable list. Our first screen was the explanatory power that a stressor exhibited for stream health indicators. Our second screen was variability across sites; a stream health indicator was included only if it exhibited a significant amount of variation that could be explained by the land-cover metrics. Our third screen required stream health indicators to contain a macroinvertebrate indicator and a water quality indicator, and the land-cover/land-use indicators to contain a metric to represent each of the three spatial scales.

From a preliminary analysis of nine stream health indicators and twenty land-cover/land-use variables, a set of a priori models was formulated for each stream health indicator. Candidate explanatory variables for the models were selected based on the student t-test ($p \leq 0.2$). The generalised least squares function was used to fit the models and maximum likelihood was used to estimate the parameters. The model with the lowest Akaike Information Criterion statistic was regarded as the "best" model, and if no model clearly stood out as the best, inferences were based on model-averaged parameter estimates. These statistical procedures guided selection of the most important explanatory metrics for stream health.

The two stream health indicators selected were a macroinvertebrate indicator (SIGNAL2, an index that assigns a score to aquatic invertebrate families based on their tolerance for pollution, with scores ranging from 1 for the most tolerant to 10 for the least tolerant, Chessman, 2003) and a physical/chemical indicator (temprange, water temperature diel range in Celsius). Additional physical/chemical health indicators exhibited insufficient variation across sites (maximum temperature), failed to respond significantly to variation in the selected land-cover metrics (conductivity, dissolved oxygen) or remained within healthy bounds at all sites (hydrogen concentration, pH).

The three land-cover/land-use metrics selected were: (1) EucDisSite, a local-scale metric for impervious surface which uses a Euclidean IDW function to give land cover closer to the site a higher weight to reflect its stronger influence on stream ecosystem health and habitat condition than land cover further from the site (Gregory et al., 1991); (2) PopDen, a census-based catchment-scale metric for population density, a lumped measure which gives equal weights to all 5 m × 5 m cells in a site's catchment area; and (3) TreeReaRip, a reach-scale metric for tree cover, specified as an areal buffer with a distance-weighting function that weights equally all cells within a 200 m upstream riparian buffer while giving zero weight to all cells outside the buffer (Van Sickle and Johnson, 2008; King et al., 2005).

PopDen was the most important catchment-scale metric for both SIGNAL2 and temprange, EucDisSite was the only important local-scale metric for SIGNAL2, and TreeReaRip was an important reach-scale metric for both SIGNAL2 and temprange. PopDen may be acting as a surrogate for other land-cover metrics such as the extent of stormwater piping, but because it is the catchment-scale metric with the most support in the data it is likely that it also captures other factors associated with increased population. PopDen and EucDisSite are analogous to the socio-economic constraints mentioned in the systematic planning literature (Hermoso et al., 2012).

The traditional way of considering land-cover impacts on ecosystem health is the addition over time of land-cover and land-use stressors associated with anthropogenic change. In the context of DEA modelling, changes to existing land-cover in urban areas (at varying costs depending on the current infrastructure level) with potential to improve stream health may be classed as "low stress inputs" required to produce "stream health outputs".

Good stream health is positively correlated with low levels of stress. However not all conventional stream health indicators are indicators of *good* health, and not all conventional stress indicators are indicators of *low* stress. Consequently, in order to maintain a positive relationship between inputs and outputs we applied three conversions to the data prior to DEA:[4]

- Temperature range was converted to temperature stability $(\text{temprange})^{-1}$ because a smaller diel temperature range enhances the growth, metabolism, reproduction and dispersal of aquatic organisms.[5]
- Population density was converted to population sparsity $(\text{PopDen})^{-1}$.
- The distance-weighted extent of impervious land cover metric was converted to $(\text{EucDisSite})^{-1}$ because the greater the distance of impervious land cover from a stream the greater is the scope for attenuation before reaching the stream (pollutants can be attenuated in the soil and hydrology impacts of stormwater flows are reduced).

Summary statistics for the good health indicators and the low stress indicators appear in Table 1. The good health indicators have satisfactory inter-quartile ratios of approximately 1.5, and two low stress

[3] Details of the GIS techniques employed to create this primary data set can be found in Millington (2014).

[4] When a data set contains both desirable and undesirable variables the analyst must make a modelling decision. We have chosen to convert indicators of bad health and high stress to indicators of good health and low stress, which allows us to use conventional DEA to create a radial performance measure. The alternative is to retain desirable and undesirable variables and employ a non-radial efficiency measurement method based on hyperbolic or directional distance functions. Färe et al. (1989) based their analysis on hyperbolic distance functions, while Bellenger and Herlihy (2009, 2010) and Macpherson et al. (2010) based their analyses on directional distance functions.

[5] Justification for this and other health indicators can be found in the Healthy Waterways 2006–2007 Annual Report at http://www.healthywaterways.org/EcosystemHealthMonitoringProgram/ProductsandPublications/AnnualTechnicalReports.aspx.

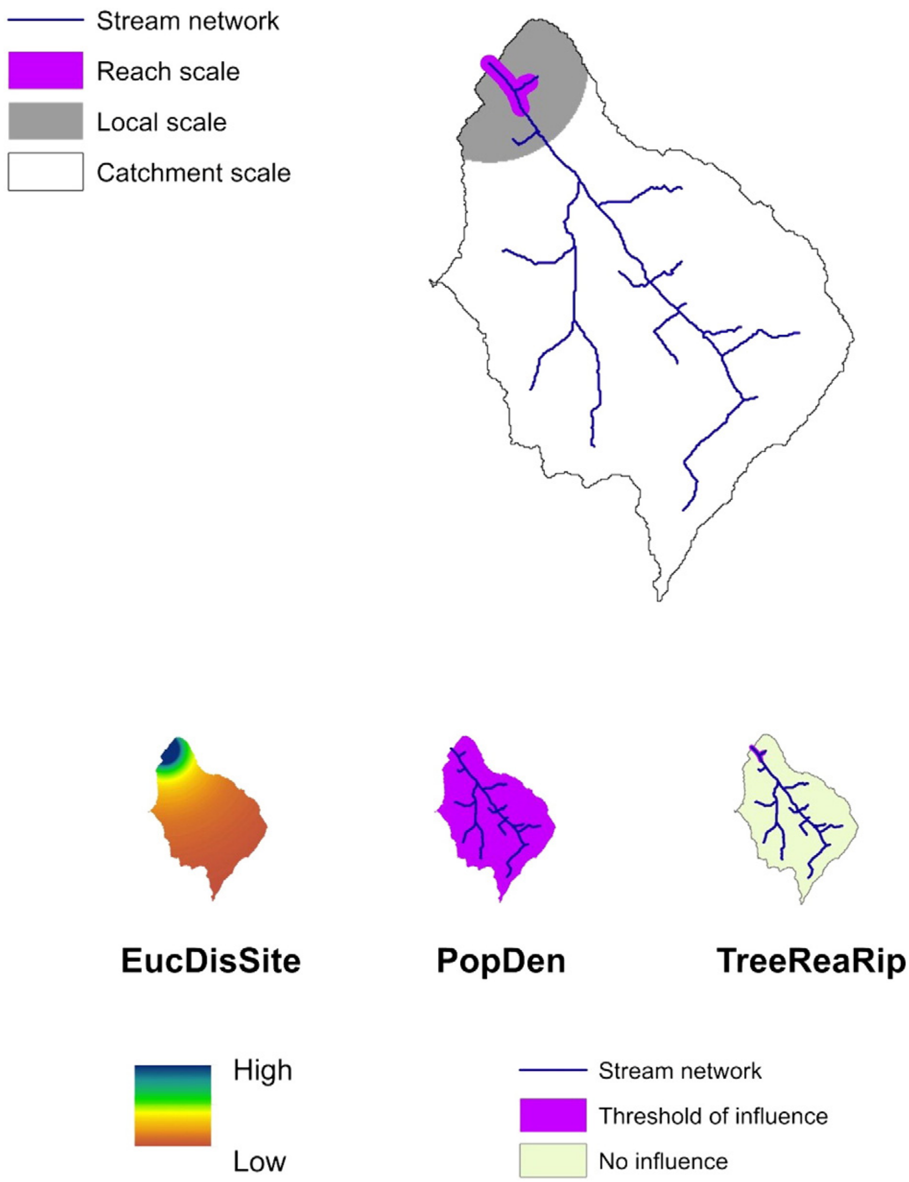

Fig. 1. Land-cover/land-use spatial scales.

Table 1
Descriptive Statistics.

Variables	Labels	Min	Q1	Mean	Q3	Max
Site good health indicators						
SIGNAL2	y_1	1.38	2.19	2.84	3.48	4.81
temprange		0.7	1.53	2.19	2.4	6.7
$(\text{temprange})^{-1}$	y_2	0.15	0.42	0.56	0.66	1.43
Site low stress indicators						
EucDisSite		0.07	0.19	0.25	0.32	0.44
$(\text{EucDisSite})^{-1}$	x_1	2.25	3.14	5.21	5.2	14.29
PopDen		2.61	14.07	15.17	17.2	21.83
$(\text{PopDen})^{-1}$	x_2	0.046	0.058	0.079	0.071	0.383
TreeReaRip	x_3	0.157	0.474	0.659	0.899	0.998
Site health index						
SHI	Y	0.37	0.52	0.67	0.84	1.00
Site low stress index						
LSI	X	1.00	1.09	1.47	1.52	3.27

indicators have larger inter-quartile ratios. Although $(\text{PopDen})^{-1}$ has a smaller inter-quartile ratio, it has a large max/min ratio.

4. Data Aggregation

Composite indicators, ecological/environmental and otherwise, are scalar-valued weighted aggregates of multiple individual indicators. Their construction requires specifying weights and an aggregator function. Ebert and Welsch (2004) exploit social choice theory to propose desirable properties of composite indicators, and Böhringer and Jochem (2007) argue that a prominent group of sustainable development indices fail to satisfy these properties. Nevertheless composite indicators are ubiquitous, with most being based on exogenous weights, although a small but growing minority is based on endogenous weights.

4.1. Index Generation With Exogenous Weights

When the objective is the aggregation of individual indicators into an ecological/environmental index, weights must be applied to each indicator to reflect its relative importance prior to aggregation. Most economic indices use market prices to weight economic indicators, but since most ecological/environmental indicators lack market prices, an alternative weighting scheme must be devised to construct an index. Some indices are particularly relevant to the present study.

The Environmental Performance Index (EPI) (Emerson et al., 2012) has since its inception tracked the environmental performance of nations. Environmental performance is measured with an index obtained by aggregating numerous diverse environmental indicators. The EPI uses arbitrary weights informed by expert judgement, a procedure followed in much of the larger composite indicator literature. However expert judgement often is missing. Hajkowicz (2006) replaced experts with stakeholders (residents and visitors), whose preferences generated weights with which to aggregate environmental indicators in the Great Barrier Reef region of Australia into a water-service index. Zhou et al. (2006), citing a lack of expert judgement, weighted three pollutants equally in constructing an air quality index for Chinese cities. In all three of these examples weights were determined exogenously, prior to and independently of the performance evaluation.

4.2. Index Generation With Endogenous Weights

There is an alternative to the use of predetermined exogenous weights provided by expert judgement, stakeholder preferences or equality in the development of aggregate indices. Models have been developed that generate endogenous weights as components of solutions to constrained optimisation problems. Linear programming is a popular way of formulating a constrained optimisation problem, and most variants of DEA are linear programmes.

DEA was originally proposed for use in the public sector, where outputs are typically non-marketed and output prices are typically missing.[6] Environmental and ecological problems fit into the missing prices framework; environmental and ecological variables are rarely priced on markets. Among the many applications of DEA to environmental and ecological problems with missing prices, a few contain unconventional production units, creative optimisation problems, and incorporate environmental indicators in different ways.

Counties served as production units for Hof et al. (2004), who sought areas with greatest potential for improving forest and rangeland condition that were under the most stress but could be improved simply by managing resource use more efficiently. Environmental impacts (undesirable forest and rangeland condition indicators such as habitat disturbance and toxic chemical releases) were specified as inputs to be minimised in the provision of human activity outputs (indicators such as timber harvest, livestock grazing and outdoor recreation).

Land parcels were production units for Ferraro (2004), who modelled conservation contracting for water quality objectives as a production activity that attempts to minimise the cost (the input) of obtaining a contract on a riparian land parcel having desirable biophysical attributes (the outputs) that contribute to the conservation goal once the parcel is secured by a contract.

Watersheds served as production units for Macpherson et al. (2010), who studied their ability to simultaneously maximise four desirable outputs (a mix of socio-economic and environmental variables including percent wetland and percent interior forest) while minimising six undesirable outputs (environmental problems including pollution and exotic aquatic and terrestrial species) and four inputs (watershed characteristics including percent impervious surface and road density).

DEA is also gaining popularity as a way of constructing environmental indexes. In an influential paper Färe et al. (2004) used DEA to construct a desirable output quantity index, an undesirable output quantity index, and an environmental performance index as the ratio of the two. The weights of the components of the two quantity indices are determined endogenously, as the normalised multipliers, or shadow prices, attached to the components in the DEA exercise.

This approach was used by Azad and Ancev (2010) to construct an environmental performance index for irrigated enterprises in the Murray–Darling Basin, Australia. Gross revenue was the desirable output and an ecologically-weighted water withdrawal indicator and a salinity impact indicator were included in the undesirable output quantity index. Their inputs were the volume of water applied and all costs excluding the cost of water.

Environmental indices that account for chemical stress and ecological response at stream sites within an eco-region of the USA were constructed using variants of DEA by Bellenger and Herlihy (2009, 2010). The indices aggregated six macroinvertebrate indicators (included in the Environmental Protection Agency's multimetric stream health index MMI) and three chemical stressors originating from non-point sources into an environmental performance index. An important contribution of the latter study is its use of normalised shadow prices, or "marginal performance estimates," to weight each of the six macroinvertebrate metrics by their observed contribution to environmental performance

An international application was provided by Zhou et al. (2007), who used a convex combination of two variants of DEA, which generated most and least favourable weights for each unit, to create a sustainable energy index for eighteen APEC countries.[7]

The use of DEA to aggregate indicators to construct output, input and performance indices has two key advantages: (i) DEA-based indices satisfy some desirable properties. They are bounded above or below by unity, monotonically increasing or decreasing, homogeneous, and independent of units of measurement. (ii) DEA does not require predetermined exogenous weights with which to aggregate indicators in the construction of an index. Endogenously generated shadow prices emerge as weights from the DEA multiplier programmes in Section 5. These weights maximise the performance of the site under evaluation in comparison with the other sites in the sample. In our context, although these weights may not reflect the consensus (if one exists) of ecologists on the relative importance of specific health and stress indicators, they do reflect the underlying processes that relate stress indicators to health indicators *in our sample of urban streams*.

5. DEA for Urban Streams

We measure the ecological performance of urban stream sites in achieving maximum stream health given the constraints imposed by land-use stressors. We model urban stream health as a production activity that converts land-cover condition at the reach, local and catchment scales into stream health. The stream site is the production unit.

In general we consider $r = 1,\ldots,s$ good health indicators y_r, $i = 1,\ldots,m$ low stress indicators x_i, and $j = 1,\ldots,N$ stream sites. In our case $r = 2$, $i = 3$ and $j = 30$. We show how to use DEA to aggregate health indicators into a health index SHI, to aggregate low stress indicators into a low stress index LSI, to construct an ecological performance index EPI, and to calculate response elasticities of the stream health index to marginal changes in each of the low stress indicators. We then describe dominator analysis, which complements the ecological performance index.

[6] In the first empirical application of DEA, Charnes et al. (1981) evaluated the performance of a U.S. public school education program ("program efficiency") and how it was managed ("management efficiency"), and distinguished the two. Over 30 years on the vast majority of empirical applications remain independent of prices, whether or not they exist.

[7] Many writers have used variants of DEA to aggregate environmental indicators to construct composite indices across countries. These environmental–economic output quantity indices are generalisations of Okun's Misery Index, Calmfors' Index and the OECD's Magic Diamond popularised by *The Economist*. The popularity of macroeconomic applications is due to the ready availability of relevant data, and to the plethora of composite indicators, an information server for which is http://ipsc.jrc.ec.europa.eu/?id=739.

5.1. A Stream Health Index

The objective is to maximise overall health at each site, regardless of the stress levels at each site. Constructing the health index SHI follows Lovell (1995), who specified this output-oriented optimisation problem as DEA Model 1, which contains no low stress indicators.

Envelopment programme		Multiplier programme	
Max ϕ_o Subject to		Min δ_o Subject to	
$\sum_{j=1}^{N} \alpha_j y_{rj} \geq \phi_o y_{ro}$	$r = 1, \ldots, s$	$\sum_{r=1}^{s} \gamma_r y_{ro} = 1$	
$\sum_{j=1}^{N} \alpha_j = 1, \alpha_j \geq 0$	$j = 1, \ldots, N$	$-\sum_{r=1}^{s} \gamma_r y_{rj} + \delta_o \geq 0$	$j = 1, \ldots, N$
		$\gamma_r \geq 0, \delta_o free$	
DEA Model 1 calculating SHI			

The envelopment programme estimates $\phi_o \geq 1$ for each site, and the stream health index $SHI_o = Y_o(y_{1o,\ldots,}y_{so}) = \phi_o{}^{-1} \leq 1$. Site health index values range downward from 1 (the healthiest sites in the sample). The stream health index is analogous to the stream health grades reported by EHMP (although they were constructed very differently) and the MMI stream condition index of Bellenger and Herlihy (2009). The variables in the multiplier programme provide estimates of the shape of a contour of the SHI frontier.

5.2. A Low Stress Index

The objective is to minimise overall low stress at each site, regardless of the health of each site. A low stress index LSI is the solution to the input-oriented optimisation problem in DEA Model 2, which contains no health indicators.

Envelopment programme		Multiplier programme	
Min θ_o Subject to		Max μ_o Subject to	
$\theta_o x_{io} - \sum_{j=1}^{N} \beta_j x_{ij} \geq 0$	$i = 1, \ldots, m$	$\sum_{i=1}^{m} \rho_j x_{io} = 1$	
		$\mu_o - \sum_{i=1}^{m} \rho_j x_{ij} \leq 0,$	$j = 1, \ldots, N$
$\sum_{j=1}^{N} \beta_j = 1, \beta_j \geq 0$		$\rho_j \geq 0,\ \mu_o\ free$	
DEA Model 2 calculating LSI			

The envelopment programme estimates $0 \leq \theta_o \leq 1$ for each site, and the low stress index $LSI_o = X_o(x_{1o,\ldots,}x_{mo}) = \theta_o^{-1} \geq 1$, so that site low stress index values range upward from 1, the most stressed sites in the sample, with increases in $\theta_o{}^{-1}$ signalling reductions in stress. The low stress index is analogous to the undesirable output quantity index of Azad and Ancev (2010). The variables in the multiplier programme provide estimates of the shape of a contour of the LSI frontier.

5.3. An Ecological Performance Index

Once a good health index and a low stress index have been calculated for each site, a third DEA model is used to measure overall ecological performance at each site. An ecological performance index EPI is the solution to the output-oriented optimisation problem in DEA Model 3.

Envelopment programme		Multiplier programme	
Max ϕ_o Subject to		Min $\delta X_o + \delta_o$ Subject to	
$\sum_{j=1}^{N} \alpha_j X_j \leq X_o$		$\gamma Y_o = 1$	
$\sum_{j=1}^{N} \alpha_j Y_j \geq \phi_o Y_o$		$-\gamma Y_j + \delta X_j + \delta_o \geq 0$	$j = 1, \ldots, N$
$\sum_{j=1}^{N} \alpha_j = 1, \alpha_j \geq 0$	$j = 1, \ldots, N$	$\delta, \gamma \geq 0, \delta_o free$	
DEA Model 3 calculating EPI			

The envelopment programme estimates the overall scope to improve $\phi_o \geq 1$ for each site. The ecological performance index is $EPI_o = EPI_o(X_o, Y_o) = \phi_o^{-1} \leq 1$, and so the ecological performance index ranges downward from 1, the highest performing sites. The variables of the multiplier programme provide estimates of the shape of a contour of the EPI frontier, and provide a measure of returns to scale at each site given by the scale elasticity $\varepsilon_{YX} = \delta X / \phi Y$.[8]

5.4. Response Elasticities

Responsiveness of SHI to marginal changes in each low stress indicator is provided by output-oriented DEA Model 4, which contains the stream health index, and m low stress indicators.

Envelopment programme		Multiplier programme	
Max ϕ_o Subject to		, Min $\sum_{i=1}^{m} \delta_i x_{io} + \delta_o$	
$\sum_{j=1}^{N} \alpha_j x_{ij} \leq x_{io}$	$i = 1, \ldots, m$	Subject to $\gamma Yo = 1$	
$\sum_{j=1}^{N} \alpha_j Y_j \geq \phi_o Y_o$		$-\gamma Y_j + \sum_{r=1}^{s} \delta_i x_{ij} + \delta_o \geq 0$	$j = 1, \ldots, N$
		$\delta_i, \gamma \geq 0, \delta_o free$	
$\sum_{j=1}^{N} \alpha_j = 1, \alpha_j \geq 0$	$j = 1, \ldots, N$		
DEA Model 4 calculating response elasticities			

The envelopment programme generates an ecological performance index based on a stream health index and three low stress indicators; we do not report this index because it is so similar to EPI. When response elasticities are the goal we focus on the multiplier programme, the variables in which describe the shape of the best-practice frontier, from which response elasticities are calculated for each site as $\varepsilon_{Yi} = \delta_i x_i / \phi Y$. These elasticities provide estimates of the sensitivity of the stream health index to marginal changes in each low stress indicator, and provide guidance to those responsible for the allocation of scarce resources.

5.5. Dominator Analysis

Efficiency analysis generates for each inefficient site a set of peers located at the vertices of the relevant facet of the frontier. An inefficient site is projected to an efficient virtual site on the interior of the relevant facet that is a convex combination of peer sites. Virtual sites and peer sites offer limited guidance on how an inefficient site can improve. A virtual site cannot be physically inspected, and peers may not dominate sites for which they are peers.

[8] A reviewer wonders whether DEA is necessary with only two variables, and whether it can be replaced with the more transparent ratio SHI/LSI. The answer is no, unless the EPI technology satisfies constant returns to scale, which requires $\delta_o = 0$ in the multiplier programme of DEA Model 3. For our data set the rank correlation between the ratio SHI/LSI and the ecological performance index EPI is just 0.494, suggesting that SHI/LSI is not a very good proxy for EPI.

Dominator analysis does not require a frontier, whereas efficiency analysis does. Dominator analysis can be based on the five indicators, but we base it on the two indices because they reveal more dominance relationships. Dominator analysis generates for each inefficient site a set of useful role model sites. A site (Y_o, X_o) dominates an inefficient site (Y_n, X_n) if it is at least as healthy despite facing at least as much stress, i.e. if $Y_o \geqq Y_n$ and $X_o \leqq X_n$. Dominating sites are not necessarily efficient sites, but they are existing sites with similar characteristics that can be physically inspected. A site that dominates many sites can provide practical guidance on how better to cope with urban stressors, and a site dominated by many sites has many role models from which to learn. Dominator analysis also can provide clues to the underlying mechanisms of stressors that impact urban stream health and help to identify factors that have been excluded from DEA models.

6. Findings and Discussion

Empirical findings are summarised in Table 2.

6.1. Stream Health Index

SHI values obtained from DEA Model 1 appear in column (1). Values range downward from 1 (the healthiest sites) to under 0.5 (the least healthy sites), revealing wide variation in health across the 30 sites, even within a catchment assigned a health grade of D- in the 2013 EHMP report.

Fig. 2 provides a spatial presentation of the variation in SHI. The Norman Creek sub-catchment is the small area bordered in pink, and the Bulimba Creek sub-catchment is the large area also bordered in pink. Healthier sites are darker, and with few exceptions (e.g. S_19, S_20), most healthy sites are upstream of unhealthy sites. Bulimba Creek sites are healthier (mean SHI = 0.70) than those in Norman Creek (mean SHI = 0.54).

6.2. A Low Stress Index

LSI values obtained from DEA Model 2 appear in column (2). Values range upward from 1 (the most stressed sites) to over 3 (the least stressed sites). An association of low stress with good health is apparent, although not all healthy sites enjoy low levels of stress (e.g., S_18), and not all highly stressed sites are in relatively poor health (e.g., S_26).

Fig. 3 illustrates the spatial distribution of LSI. Darker areas have relatively low stress. Norman Creek is generally more stressed (mean LSI = 1.22) than Bulimba Creek (mean LSI = 1.53), which is consistent with our finding that it is less healthy. The eastern side of Bulimba Creek is generally least stressed, which is consistent with it being the least developed. Impervious surface area in the Norman Creek sub-catchment is higher than in the Bulimba Creek sub-catchment. Norman Creek also has extensive sections of its creek network piped, and unlike Bulimba Creek, it does not have most of its main channel maintained as free flowing channel with a relatively natural riparian zone.

6.3. An Ecological Performance Index and Dominator Analysis

Scope to improve ϕ and EPI $= \phi^{-1}$ obtained from DEA Model 3 appear in columns (3)–(4). EPI values range downward from 1 (high-performing sites) to under 0.5 (sites having the most scope to improve). Most high-performing sites are healthy, but S_26 faces the highest stress levels in the sample and has average health. Conversely, most poor-performing sites are unhealthy, regardless of the stress they face, although S_20 is a poor performer despite having nearly average health.

Scale elasticities ε_{YX} in column (5) indicate that health at relatively stressed sites is likely to respond more than proportionately to reductions

Table 2
Empirical findings.

Site ID	Y = SHI	X = LSI	ϕ	ϕ^{-1} = EPI	RTS = ε_{YX}	# sites dominating this site	# sites this site dominates	ε_{Y1}	ε_{Y2}	ε_{Y3}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
S_01	0.89	1.46	1.10	0.91	0.12	1	6	0.06	0.00	0.00
S_02	0.49	1.08	1.61	0.62	1.83	5	4	0.00	2.30	0.00
S_03	0.61	1.08	1.32	0.76	1.49	2	10	0.00	1.87	0.00
S_04	0.71	1.21	1.25	0.80	1.30	1	9	1.71	0.00	0.00
S_05	0.84	1.25	1.09	0.92	1.09	0	11	1.41	0.00	0.00
S_06	0.37	1.11	2.17	0.46	2.43	8	1	3.30	0.00	0.00
S_07	1.00	3.26	1.00	1.00	0.00	2	1	0.00	0.00	0.00
S_08	0.59	1.49	1.67	0.60	0.19	9	0	0.00	0.53	0.29
S_09	0.68	1.94	1.47	0.68	0.00	8	0	0.10	0.00	0.00
S_10	1.00	3.27	1.00	1.00	0.00	3	0	0.00	0.00	0.00
S_11	0.65	1.14	1.28	0.78	1.40	1	8	0.00	1.74	0.00
S_12	0.56	1.00	1.33	0.75	1.60	2	10	2.27	0.00	0.00
S_13	0.51	1.00	1.47	0.68	1.76	3	6	4.62	2.25	0.00
S_14	0.62	1.00	1.19	0.84	1.44	1	16	0.00	3.76	0.00
S_15	0.83	1.53	1.18	0.85	0.14	3	2	0.00	0.13	0.00
S_16	0.61	1.85	1.64	0.61	0.00	10	0	0.00	0.21	0.00
S_17	1.00	2.40	1.00	1.00	0.00	1	2	0.00	0.00	0.00
S_18	0.96	1.33	1.00	1.00	0.11	0	9	0.05	0.00	0.00
S_19	0.37	1.14	2.27	0.44	2.49	9	0	3.36	0.00	0.00
S_20	0.44	1.32	2.17	0.46	2.08	13	0	0.39	0.00	0.33
S_21	1.00	1.81	1.00	1.00	0.13	0	5	0.25	0.00	0.17
S_22	0.52	1.05	1.49	0.67	1.72	3	7	0.16	11.33	0.00
S_23	0.55	1.48	1.75	0.57	0.20	11	0	0.32	0.00	0.34
S_24	0.50	1.08	1.59	0.63	1.80	6	4	0.00	0.00	2.82
S_25	0.45	1.30	2.08	0.48	2.03	12	1	0.00	2.46	0.00
S_26	0.74	1.00	1.00	1.00	1.21	0	20	0.00	1.54	0.00
S_27	0.51	1.41	1.89	0.53	0.21	11	0	0.00	0.00	0.37
S_28	0.59	1.27	1.56	0.64	1.54	6	6	2.01	0.00	0.00
S_29	0.58	1.40	1.67	0.60	0.18	8	2	0.28	0.00	0.26
S_30	0.84	1.53	1.18	0.85	0.14	3	2	0.06	0.00	0.00
Mean	0.67	1.47	1.45	0.74	0.96	5	5	0.68	0.94	0.15

Elasticities: 1 = $(\text{EucDisSite})^{-1}$, 2 = $(\text{PopDen})^{-1}$, 3 = TreeReaRip.

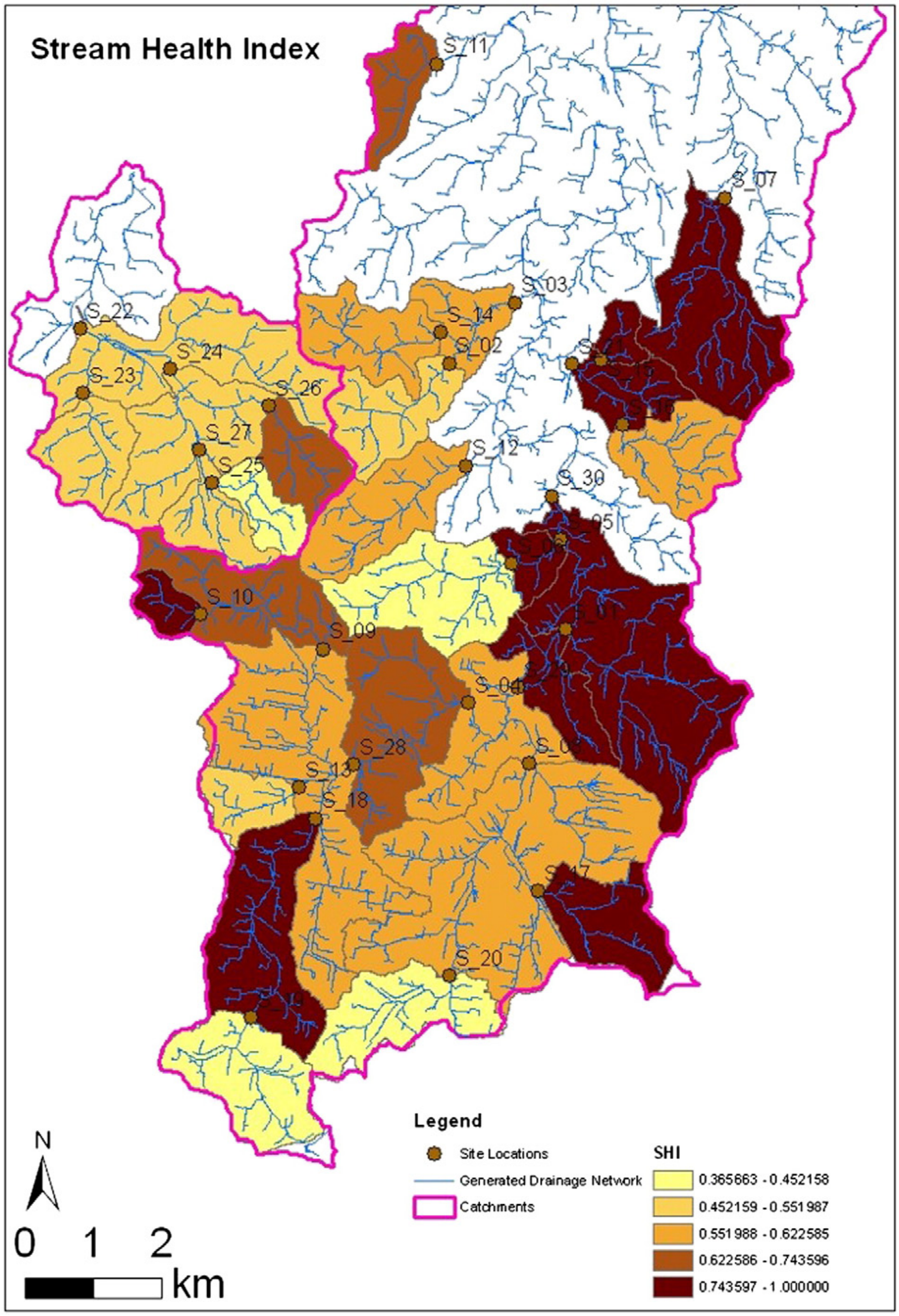

Fig. 2. The spatial arrangement of the stream health index.

in stress, and that health at less stressed sites is likely to respond less than proportionately to reductions in stress.

Dominator information appears in columns (6)–(7). Site S_26 dominates the most sites, and five sites are dominated by ten or more sites. Of the five most dominant sites, only S_26 is a best-practice site. Conversely, of the six best-practice sites, four dominate very few sites. This emphasises the independence of dominator analysis and efficiency analysis; one is neither necessary nor sufficient for the other. The two techniques provide complementary information.

The spatial distribution of EPI values appears in Fig. 4. Darker areas are relatively high-performing sites, including S_26, which is one of the most stressed sites (LSI = 1) but is moderately healthy (SHI = 0.74). S_07, S_10, S_17 and S_18 also have EPI = 1. S_07, S_10 and S_17 are headwater sites or small tributaries with no sampled sites further upstream. S_07 and S_10 are the two least stressed sites in the study.

Apart from S_26, Norman Creek sites as a whole generally underperform (mean EPI = 0.57) Bulimba Creek sites (mean EPI = 0.80), which is consistent with Bulimba Creek sites being healthier and under less stress. One factor that a visual inspection of sites highlights is the amount of stream network fragmented and piped underground in Norman Creek.

6.4. Responsiveness of Health to Variation in Stress

Response elasticities calculated from DEA Model 4 appear in columns (8)–(10), and provide two types of information relevant to the efficient allocation of resources: (1) mean values give a general idea of which stressor is most strongly associated with stream health in the sample; and (2) values for an individual site indicate which stressor is

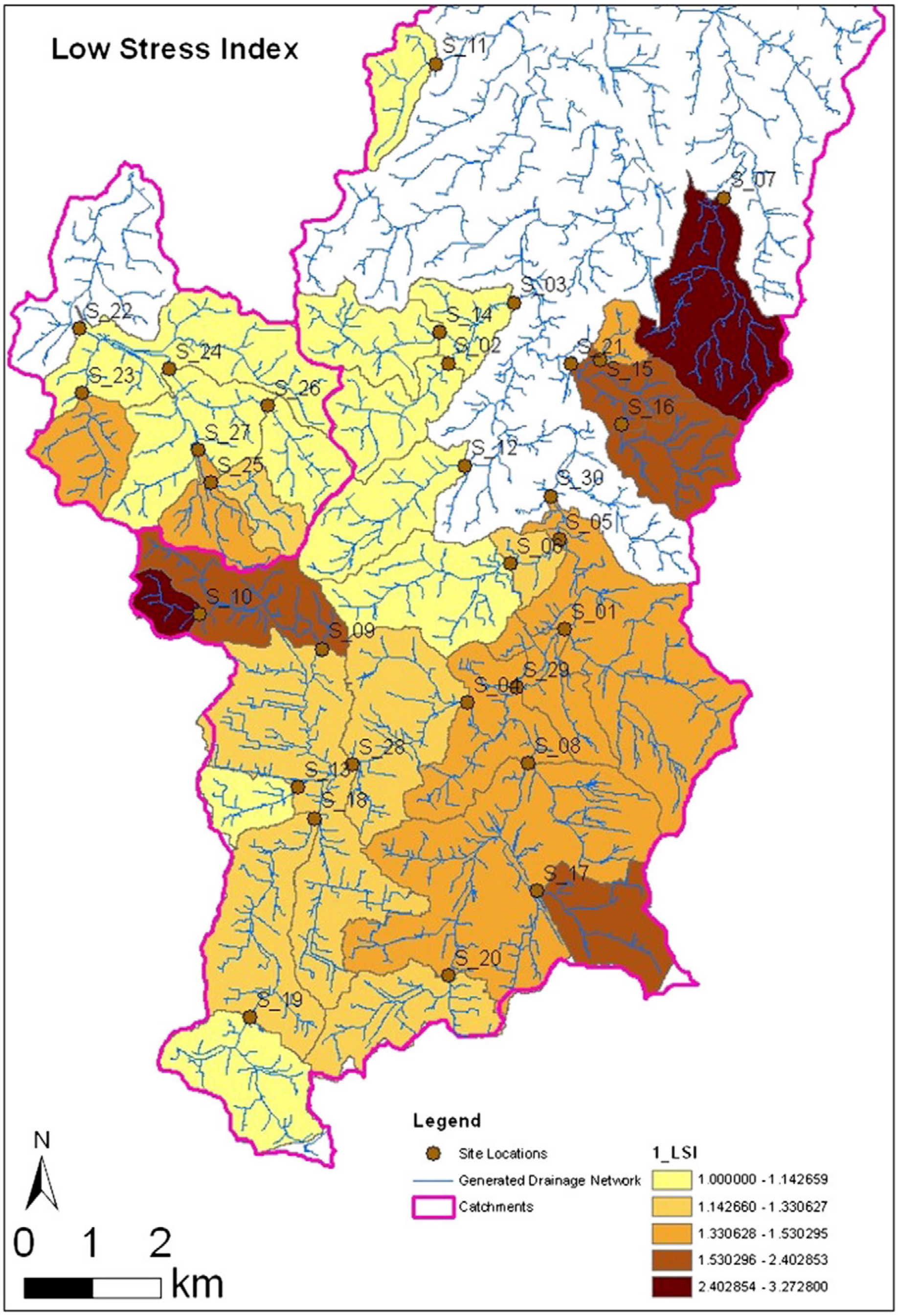

Fig. 3. The spatial arrangement of the low stress index.

most strongly associated with its health. Elasticity values above one indicate greater than proportional potential health gains.

The mean elasticities indicate that stream health is moderately responsive to marginal changes in $(\text{PopDen})^{-1}$ and $(\text{EucDisSite})^{-1}$, and barely responsive (with one exception) to marginal changes in TreeReaRip. The response elasticities at specific sites illustrate the heterogeneity of sites and suggest that some sites are most responsive to marginal changes in $(\text{EucDisSite})^{-1}$, others to marginal changes in $(\text{PopDen})^{-1}$, and just two to TreeReaRip.

6.5. Health v. Performance

We noted in the introduction that Healthy Waterways operates EHMP, which monitors the health of SEQ waterways using a broad range of health indicators. EHMP does not incorporate stress indicators when it assigns grades. We have calculated a rank correlation coefficient between SHI, which ignores stress, and EPI, which incorporates stress, in order to determine whether failure to incorporate the stresses confronting urban streams, as EHMP does, paints an inaccurate picture of their relative performance.

Based on the rank correlation coefficient (0.92), the answer is no, but with some large discrepancies. Stream health tracks stream performance fairly well, especially when low stress indicators are aggregated to a low stress index that smooths out some of the variability in the component indicators. For example, site S_26 is a star performer, on the frontier and dominating 20 sites, yet its health, as measured by SHI, would warrant a grade of C+ on its report card. In contrast, the performance of frequently dominated sites

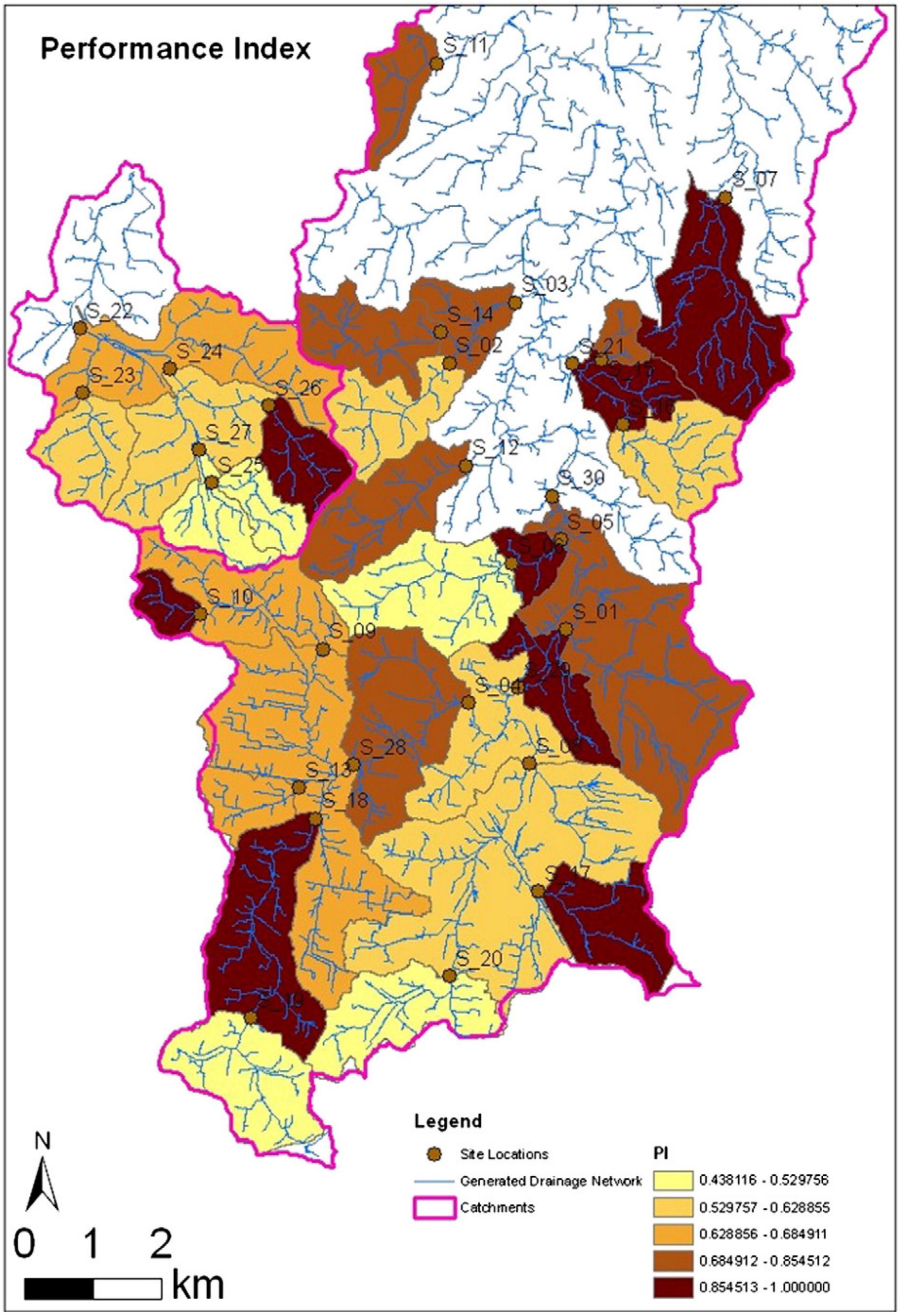

Fig. 4. The spatial arrangement of the ecological performance index.

S_08 and S_16 is overstated by their health index because they are under relatively little stress.

7. Conclusions

Brisbane City Council (2011, 2013) (BCC) is interested in data supporting decision-making for new developments that support ecological, environmental, economic and social benefits for Norman Creek. We have generated and analysed one such primary data set.

We used fieldwork to create nine health indicators and GIS to create 20 land-cover/land-use indicators at 30 highly urbanised stream sites, statistical techniques to reduce the indicators to two and three, respectively, and DEA to aggregate these indicators into scalar-valued health and stress indices. The ecological performance of the 30 sites was evaluated using both DEA and dominator analysis.

We have generated three guides to assist those seeking to target sites for rehabilitation. One guide is the identification of high-performing sites that can serve as role models for under-performing sites most in need of attention. Another guide is the pattern of scale and response elasticities, which identify sites that are most likely to respond more or less proportionately to rehabilitation efforts directed at one or more stressors. A third guide is GIS mapping of ecological performance that can assist in locating sites most suitable for rehabilitation. Collectively they constitute the framework in the title of our paper.

Our research has prompted a search for potentially influential aspects of land cover or land use that were unaccounted for in the model.

EPI and dominator analysis led us to conclude that in-stream longitudinal connectivity varied noticeably among sites, and appeared to be especially low for Norman Creek sites, in which extensive sections of the stream network are buried or fragmented by concrete and stormwater piping. This process led us to conjecture that: (1) the chemical and physical processes of the riparian zone which protect stream health are compromised by the pervasiveness of stormwater piping in highly urbanised streams; and (2) ecological connectivity relating to dispersal paths and habitat fragmentation is an important factor influencing the health of highly urbanised streams (Millington, 2014).

The pattern of response elasticities, and the numerous zero values, lent support to the two conjectures and suggested the presence of additional stress factors. For example, the 200 m reach-scale riparian zone of site S_16 is almost totally tree-covered, its response elasticity is zero, and yet it is an unhealthy under-performing site. The low response elasticities for tree cover at most sites suggest that marginal improvements to reach-scale tree cover alone would have minimal effect on stream health.[9]

To test these conjectures our GIS metrics were subsequently refined. Our measure of impervious surface captures the impervious land cover near the site. More targeted land-cover metrics, such as percent piped channel in the entire mapped upstream "effective" riparian buffer 30 m either side of the stream that captures the loss of stream and riparian zone to underground stormwater piping and the fragmentation and loss of habitat which that may cause, were developed to shed further light on the underlying stress mechanisms.

Our research raises questions for those tasked with allocating resources to optimise improvement in stream health. How do some of the more highly stressed sites manage to be relatively healthy? Why are some of the relatively low stressed sites relatively unhealthy? Which sites are likely to be most responsive to which rehabilitation efforts? Observing the situation at best-practice and dominator sites enables one to get an idea of what improvements are feasible for the less efficient sites, how they might be achieved, and at what cost. Budgets are limited, and rehabilitation costs vary widely, depending on the extent of ecological connectivity and stormwater piping, among other factors (Millington, 2014).

This analytical approach differs from typical monitoring programmes which rank sites based on their health, and where healthier sites typically have lower levels of identified stressors. With this in mind, it would be desirable to narrow the analytical and data gaps between our study and EHMP. We already have noted the analytical gap between health and performance. It would be useful to collect and analyse data over both seasons, as EHMP does, on an expanded suite of health indicators used by EHMP, for these and additional sites. This study included two (water quality and macroinvertebrates) of five categories of stream health measures covered by the EHMP. The EHMP study was only partially concerned with urban streams but some of their indicators are still relevant. There are also other metrics related to urban sites that are not collected by the EHMP such as heavy metals that may be available in other urban stream data sets such as those captured by BCC and other urban councils.

Urban streams are complex systems, with multiple factors interacting at several scales, making it difficult to identify critical stressors and their relationships to urban stream health. By comparing the relative ability of similar sites to withstand the stresses caused by an urban environment, DEA and dominator analysis provide the foundation for further analysis, both through their useful findings and through their identification of potentially important missing indicators. This assessment provides a starting point for considering local- and catchment-scale health, stress, and rehabilitation priorities for these streams, which could form part of ad hoc or systematic planning approaches.

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[9] The multiplicity of zero elasticities is also an artefact of the mathematical structure of DEA, which allows sites to attach non-negative weights to their health and stress indicators that maximise their performance.

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