Quantifying Human Well-Being for Sustainability Research and Policy

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Quantifying human well-being
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Abstract.   To address human dependence on natural resources and anthropogenic impacts on ecosystem health, understanding and management of the linkages between nature and human well-being (HWB) are urgently needed. One fundamental barrier is the lack of quantitative indicators and models that integrate HWB with direct and indirect drivers of change in natural resources. While primary surveys provide the most valid HWB measures, extensive new data collection is often costly, especially for large-scale studies. Therefore, it is vital to develop methods and indices based on existing data (e.g., census data, survey data) for real-world application. To address this, we propose a new method of using structural equation modeling to construct robust, spatially explicit HWB indices from existing data and demonstrate its validity and usefulness in Cambodia. Our method is scale-free and applicable to different frameworks and data sources and thus supports relatively easy replication in many other contexts. Further application and refinement could improve understanding of human–nature interactions, move toward robust theory development, and guide natural resource management decisions.

Key words: *Cambodia; composite index; poverty alleviation; structural equation modeling; sustainable development; vulnerability and resilience.*

Introduction

Improving and sustaining human well-being (HWB) is the ultimate goal of human development. However, expansion and intensification of anthropogenic influence over the past decades has caused tremendous ecosystem degradation and environmental changes from local to regional, national, and global scales, posing severe threats to the resources on which human society depends (MA 2005). Consequently, there is a wide and growing recognition of the urgent need to understand and manage the linkages between nature and HWB (Carpenter et al. 2009, TEEB 2010, Yang et al. 2013*b*, Bottrill et al. 2014, Ruckelshaus et al. 2015). Achievements of global poverty alleviation and sustainable development goals depend on the ability to monitor HWB to track policy outcomes and the linkages between nature and HWB (Sachs et al. 2009, Turner et al. 2012). To move toward the long-term goal of developing robust theories and demonstrations of sustainability science (Clark 2007, Carpenter et al. 2009), quantitative

indicators and models (Smith et al. 2013, Yang et al. 2013*d*, 2015*b*, Ferraro and Hanauer 2014) are indispensable to the examination of hypotheses and to the understanding of the causal mechanisms of the manner in which humans interact with nature.

Recently, there has been burgeoning interest in quantifying and mapping different types of ecosystem services (ES) at multiple scales and across various kinds of ecosystems (Yang et al. 2008, TEEB 2010, Chang et al. 2011, Kareiva et al. 2011, Yang et al. 2015*a*), yet there is also a crucial need for quantitative methods and state-of-the-art HWB indices for sustainability research and the design and evaluation of policies. Scholars and policy makers are also eager to understand how policies affect natural resources and, in turn, HWB (Li et al. 2013, Liu et al. 2013, Liu and Yang 2013, Yang et al. 2013*c*, Bottrill et al. 2014), as well as how changes in HWB may alter human behaviors and consequently affect natural resources (Dietz et al. 2009, Yang et al. 2013*b*, Milner-Gulland et al. 2014). Efforts to measure HWB are not new, but many previous measures of HWB were qualitative, and existing quantitative studies often covered only a subset of HWB components (e.g., economic, sociopsychological, and health components; Carpenter et al. 2009, Villamagna and Giesecke 2014). Moreover, most previous attempts to measure HWB,

especially those prior to the Millennium Ecosystem Assessment (MA; MA 2005), failed to recognize linkages between nature and HWB. Some examples include the Life Satisfaction Index (Adams 1969, Vemuri and Costanza 2006), the Happy Planet Index (Abdallah et al. 2012), and the Human Development Index (UNDP 2013). Some recent indices, such as the Genuine Progress Indicator (Bagstad et al. 2014), the Inclusive Wealth Index (Duraiappah and Muñoz 2012), and the Better Life Index (OECD 2013), have recognized the role nature plays in human society. However, they were not designed to improve the understanding of linkages between nature and HWB, despite global interest. For instance, requests for the quantification of the manner in which changes in ecosystems and ES affect local livelihoods occurred across all sites of the Natural Capital Project (Kareiva et al. 2011, Ruckelshaus et al. 2015).

A few initial efforts have attempted to improve the understanding and measurement of HWB by revealing the ecological embeddedness of HWB. Summers et al. (2012) emphasized the contribution of nature to HWB by classifying HWB into four dimensions (also called domains, constituents, or elements) as basic needs, economic needs, environmental needs, and subjective happiness. Smith et al. (2013) proposed a framework to construct HWB indices for the United States through identifying nine HWB dimensions (i.e., health, social cohesion, education, safety and security, living standards, leisure time, spiritual and cultural fulfillment, life satisfaction and happiness, and connection to nature) and conceptually discussed their relationships to ES. Milner-Gulland et al. (2014) proposed a Well-being in Developing Countries (WeD) framework that identified three dimensions (i.e., meeting needs, pursuing goals, and quality of life) for individual well-being and advocated the application to impact evaluation of conservation interventions. These efforts all recognized the objective and subjective properties of HWB and discussed the contribution of nature to different dimensions of HWB.

Nevertheless, these initial efforts lack empirical demonstration (Busch et al. 2011, King et al. 2014). In addition, these frameworks are not conceptualized spatially and are not suitable for spatially explicit analyses of linkages between nature and HWB at subnational scales. Finally, these frameworks all required substantial new survey data collection efforts for subnational analyses, although they might use subjective indicators, such as life satisfaction, for national-level analyses (Vemuri and Costanza 2006). While customized primary data can provide high validity of HWB constructs, such data are generally too costly to collect over broad scales (Yang et al. 2013a). In practice, our ability to adequately and efficiently measure HWB will depend critically on methods and indices based on existing data sets (e.g., census data, second-hand survey data), complemented, if necessary, by targeted new data. In sum, quantitative measurements of HWB require conceptual frameworks that incorporate the ecological embeddedness and objective and subjective properties of HWB; operable frameworks that allow spatially explicit analyses and quantitative causal inference for hypothesis testing (e.g., identifying different pathways for causal mechanisms) toward robust theory development; and cost-efficient methods and indices that primarily utilize existing data with limited new data collection.

We propose a new method that addresses each of these three challenges and empirically demonstrate the procedures (Fig. 1) and initial applications. To demonstrate our method, we chose Cambodia as our study area for several reasons (a detailed description of Cambodia is given in *Materials and methods*). Cambodia exemplifies a country with high human dependence on natural resources and high levels of poverty (Ministry of Planning 2010). There are limited government capacities and environmental and socioeconomic data, yet increasing demand for sustainability research and policy interventions. Therefore, if our method proves to be viable for places such as Cambodia, with relatively poor data, it would also be feasible for other places with better data. Finally, our organization has been working in Cambodia for many years. Existing institutional knowledge of local contexts and established networks with the Cambodian government and field assistants help us to conceptualize and evaluate our analyses.

For the conceptual framework, we use the MA framework for two main reasons. One is that it is by far the most widely used framework and satisfies the objectives of our research by providing a categorization of HWB and linking each HWB component to ES. The other is that it worked well for a previous study using a similar method with primary survey data for constructing HWB indices at the local scale (Yang et al. 2013a). Therefore, we follow MA's definition of HWB as the physical and mental satisfaction a human needs to be healthy, happy, and prosperous (MA 2005, Yang et al. 2013a). Accordingly, poverty, broadly defined, is a low state of HWB. We use the MA framework (MA 2005), which categorizes HWB into five dimensions (Fig. 2): basic material (i.e., basic material for a good life), security, health, social relations, and freedom (i.e., freedom of choice and action). Our developed HWB index system thus includes an overall composite index and five subindices.
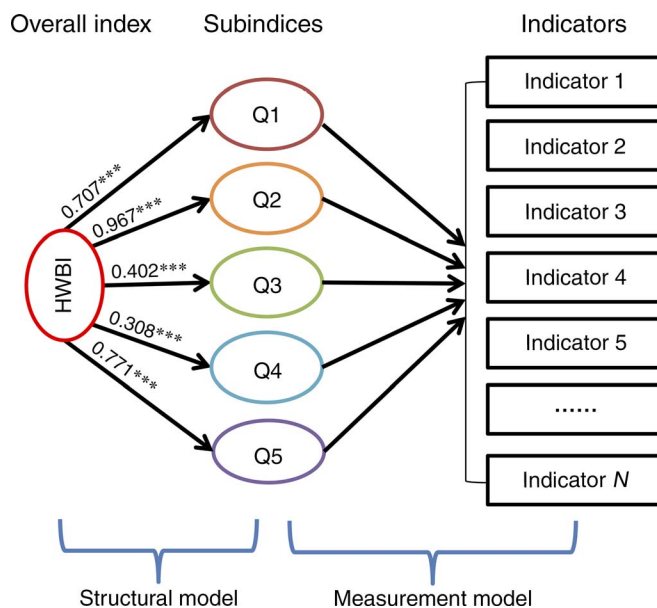
Materials and Methods

Description of demonstration site

Our HWB indices use annual data from the Cambodia Commune Database from 2006 to 2012, which compiles 34 shared indicators (i.e., indicators measured in
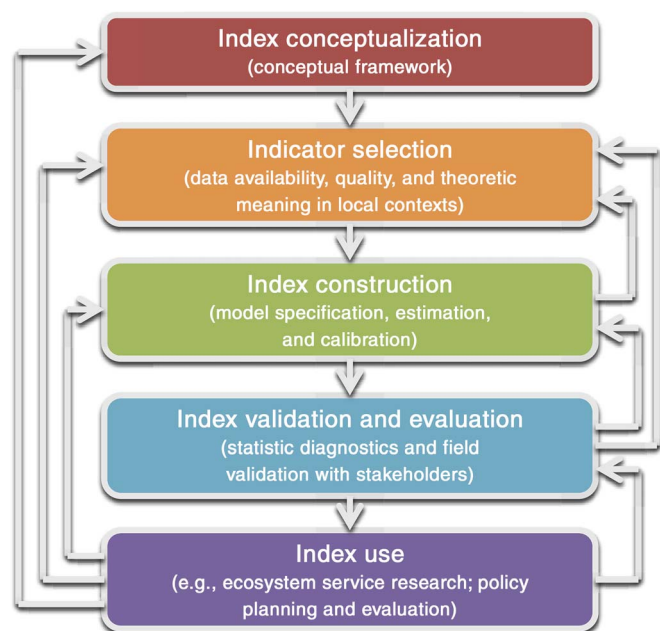
Fig. 1. General procedures for developing and applying the human well-being (HWB) indices. Arrows represent the flow direction of procedures and often are iterative processes.

Fig. 2. Path diagram of the structural equation model. Arrows indicate the direction of regressions from dependent to independent variables. Numbers on paths represent the respective standardized coefficients. Detailed descriptions of indicators used are shown in Appendix B: Tables B1–B5. Full model results, including the paths and coefficients of the structural model, are shown in Appendix D: Table D1. Abbreviations are HWBI, overall human well-being index; Q1, basic material for good life; Q2, security; Q3, health; Q4, good social relations; and Q5, freedom of choice and action.

multiple years) across years for each of the country's 1633 communes (Ministry of Planning 2010). Cambodia (Appendix A: Fig. A1) is a tropical, Southeast Asian country with a total land area of 181 035 km^2. It is characterized by a low-lying central plain surrounded by low mountains and highlands, with the Tonle Sap Lake embedded and the Mekong River flowing from north to south. As of 2013, its total population was 15.2 million, of which more than 80% live in rural areas and 30% were illiterate. It is among the poorest countries, with up to 18% of the population living on less than US$1.25 per day, ranking 138th of 187 evaluated countries in the Human Development Index as of 2013 (UNDP 2013). The well-being of Cambodians substantially depends on a wide range of ES, ranging from fish, clean water, non-timber forest products (e.g., liquid resins, palm oil, cashew, cassava), flood protection, sediment control, and carbon sequestration to ecotourism and religious values (McKenney and Tola 2002, McKenney et al. 2004). The Tonle Sap Lake and Mekong River are particularly important to Cambodians for the provision of various ES. For example, Cambodians on average consume 27–38 kg fish·yr^{-1}·person^{-1}, accounting for 40–90% of their animal protein (McKenney and Tola 2002). But their livelihoods are facing strong threats, such as dam construction along the Mekong River and rapid biodiversity loss and ecosystem degradation (Dugan et al. 2010, Ziv et al. 2012), with an annual deforestation rate of approximately 1% from 2000 to 2010 (Hansen et al. 2013).

Data

The Cambodia Commune Database is similar to census data and is an information system developed by the Ministry of Planning of Cambodia and several partners to support policy planning, fund allocation, and development (Ministry of Planning 2010). Based on data book records, the data are reported by village chiefs and commune/quarter (*khum/sangkat*) clerks to capital and provincial departments of planning every December, with a set of indicators gradually increasing in number (from 105 indicators in 2002 to 1083 indicators in 2012), covering a wide range of demographic, social, and economic conditions. A commune/quarter is an administrative unit larger than a village and smaller than a county. In 2012, there were 1633 communes (specific numbers may vary a bit in different years due to administrative adjustments), with size varying from 0.05 to 2337.16 km^2, with mean and median of 111.91 and 44.38 km^2, respectively.

We recognized the possibility of data quality concerns (e.g., measurement errors, data entry errors) for second-hand data, such as the commune database. Thus, we conducted a set of data quality control and preparation procedures before formal analyses. First, we did an initial check of indicator codes and names and wrote programming scripts to link indicators between differ-

ent years' databases. We also identified shared indicators available across multiple years through this process. Second, we conducted statistic diagnostics (e.g., basic statistic description, linear regression) and visual plotting to identify extreme points (e.g., outliers, leverage points) and other entry errors. We first compared and checked indicators across years and then scrutinized suspicious points across all observations within each year. For distance-related indicators, we also verified their ranges using Euclidean distance in ArcGIS software (version 10.2; ESRI, Redlands, California, USA). For systematic errors (e.g., unit entry error), we corrected them accordingly. For unsystematic errors (e.g., outliers with no reasonable remedial solutions), we removed those observations. Third, we aggregated village-level indicators to the commune level. Depending on the nature of specific indicators, some were aggregated using their mean values (e.g., distance from each village center to the nearest primary school), while others were aggregated using their summed values (e.g., population, number of bicycles). Fourth, for aggregated indicators at commune level, we repeated the second procedure described previously. Fifth, given that some indicators have many zero and null values, we implemented another special quality control for these indicators. Some indicators inherently have many zero values (e.g., murder rate), while for some other indicators, the inclusion of many zero and null values in the raw data indicate poor data quality. Thus, after examining the distribution of zero and null values in the database, we set a relatively conservative threshold and identified those indicators that have >15% zero and null values, but which should not inherently have >15% zero and null values, as indicators with relatively poor quality. Finally, after we obtained the preliminary results of HWB indices, we repeated the second procedure again to check whether some communes had extreme values of HWB indices; if they did, we double-checked the original data points again and made standard corrections as mentioned previously. Then, we ran the model again for updated HWB indices. In sum, through all the quality control approaches, we believe that we ensured the quality of data used for this study. We used only the final, clean data of high quality for our analyses.

Given there are fewer shared indicators that are suitable for HWB indicators from 2002 to 2005 with comparison to those from 2006 to 2012, we decided to work with data from 2006 to 2012 to demonstrate our method. Because different communes may have varied demographic and socioeconomic conditions, to ensure that indicators are comparable across communes, we calculated the per capita values, per family values, or other rates that facilitate comparison. We also aggregated some similar indicators (e.g., houses with television by different types of roofs) into one indicator when necessary. Finally, according to data availability, data

quality, and theoretic meaning (because some indicators are not relevant to HWB), we selected 34 indicators (Appendix B: Tables B1–B5) from 2006 to 2012 to construct the HWB indices. Specifically, we regarded an indicator as theoretically meaningful for HWB based on our HWB definition buttressed by the theory of human needs (Maslow 1943, Doyal and Gough 1991). In the Cambodian context, if an indicator represents the satisfaction of any human needs either physically or mentally, it is considered a meaningful indicator for HWB. A brief justification of theoretical meaning is given for each indicator in Appendix B: Tables B1–B5.

Index development and evaluation

The validity of ex post facto human well-being (HWB) indices may be reduced by the fact that secondary data are unlike designed or experimental data with prearranged instruments for an HWB index system. To cope with this challenge, we developed a new method by combining theoretic design with data maximization via structural equation modeling (SEM). SEM is an established and powerful statistical technique allowing the test and estimation of causal relations among statistical data based on qualitative assumptions (Wright 1921, Brown 2006, Hoyle 2014). The general form of SEM includes a structural model (expressing potential causal relations between endogenous and exogenous variables) and a measurement model (representing the paths between latent variables and indicators measuring them). Due to its ability to construct latent variables (i.e., variables not observable or directly measurable), besides being widely used for causal inference, SEM is also often used for developing composite indices (Brown 2006, Schmitt 2011, Hoyle 2014). In brief, we used SEM to link selected indicators to the five HWB dimensions for subindices and then the overall composite index (Fig. 2). By adding or removing paths in the measurement model based on theoretic meaning and statistical tests, we can adjust the obtained HWB indices. Through the iterative process of validating HWB indices internally in the lab and externally in the field, as well as calibrating the paths in SEM based on validation feedback, we can obtain a set of optimized (or near-optimized) HWB indices with high internal and external validity.

Specifically, we first proposed an initial design and then conducted confirmatory factor analysis (CFA). We conducted reliability tests to examine the internal consistency of this initial design, which is relatively high (Appendix C: Tables C1–C5). We realized that one indicator for one dimension of HWB might also be a good indicator of another dimension, which is a common issue for composite index development (Nardo et al. 2005, Brown 2006, Schmitt 2011, Hoyle 2014). For example, the roof type of a house is often a good indicator of the basic material dimension, but also could

be a good indicator for the security, health, and freedom of choice and action of a rural household. Therefore, the initial design might be further refined through maximizing the use of each indicator by including the omitted paths. Specifically, we used the modification indices (i.e., Lagrange multiplier tests for the statistical significance of omitted paths). We then used exploratory factor analysis (EFA) to refine the design iteratively by adding or removing certain paths. Only paths that were both theoretically meaningful and statistically significant were kept in the final model. The CFA and EFA, as well as factor analysis, regression analysis, and path analysis, are all special forms of SEM (Pearl 2009, Bollen and Noble 2011). The major difference between the two is not, as their names might suggest, that one is only confirmatory and the other is only exploratory. Rather, the major difference in practice is that CFA usually does not include cross-loadings (i.e., one indicator loads to multiple dimensions) unless a priori cross-loadings are hypothesized, while EFA does include them (Schmitt 2011). More detailed technical notes and discussion of SEM (e.g., handling multiple indicators for multiple factors without double counting, since SEM estimates multiple linear equations simultaneously) can be found in Brown (2006) and Hoyle (2014).

We evaluated the results of HWB indices through standard statistical tests, initial applications, and field evaluations with stakeholders. First, the reliability test of internal consistency of the index system provided evidence of internal validity. Second, the statistic indices of SEM offer secondary evidence for internal validity. Third, the initial applications of HWB indices provide external support of the validity. Finally, we presented the temporal and spatial patterns of HWB indices, as well as results of initial application of HWB indices, in a workshop held in June 2014 in Cambodia to a wide range of stakeholders (e.g., external researchers, field staff, government officials, and citizen representatives). Many of these stakeholders are people who are familiar with the context of Cambodia and have been collaborating with our country program for years. To avoid potential bias from people who participated in the data collection, none of them were invited to evaluate the HWB indices. We were also not aware of any tendency of participants to validate or invalidate the results. We requested that participants evaluate the design and temporal and spatial dynamics of HWB indices, offer context-based explanations of the results, and provide comments and suggestions for refinement. Taking the insights of the stakeholders into consideration, we revised the index design, model, and interpretation of results accordingly.

We implemented the SEM in the software Mplus (version 6.1; Muthén and Muthén, Los Angeles, California, USA). We conducted all the data management programming and additional statistical analyses using the software Stata (version 12.0; StataCorp, College Station, Texas, USA). We normalized index values of each dimension separately to the range 0–100 using the minimum–maximum normalization method based on data in all years so that indices of the same dimension are comparable across years. We mapped the HWB indices in ArcGIS.

Results

Overall, statistical results show that our derived HWB indices have very high internal validity and represent the temporal and spatial patterns in our demonstration area well. Results of the initial applications of the HWB index system with local experts and stakeholders demonstrate the indices' external validity and utility for analysis and decision making.

Internal validity of derived HWB indices

Reliability and goodness-of-fit statistics show that the method of combining theoretic design with data maximization provides refined and valid indices. Generally, it is regarded as an internally consistent design if the item–total correlations are larger than 0.3 and the Cronbach's alpha values are higher than 0.6 (Nardo et al. 2005). Compared to the initial theoretic design, the refined design from SEM shows an overall improvement in internal consistency. Most indicators (see detailed description in Appendix B: Tables B1–B5) that were included in the refined design from SEM have item–total correlations higher than 0.3 (Appendix C: Tables C1–C5). Particularly, for all five HWB dimensions, the Cronbach's alpha values increased from the initial design to the refined design (Table 1).

Model-fit statistics of the HWB indices all suggest an adequate fit, regardless of the goodness-of-fit measure used (Table 2). Specifically, the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) are 0.959 and 0.944, respectively. Both the root mean square error of approximation (RMSEA) and standardized root mean square residual (SRMR) are much lower than the target criterion of 0.05. In addition, we only included those indicators from the commune database that have theoretic meanings for HWB and that also show statistical significance. Thus, all the paths linking indicators from the commune database to HWB dimensions via the SEM have significant coefficients and also significantly contribute to model fit (Fig. 2; Appendix D: Table D1).

Temporal and spatial dynamics of the HWB indices

Overall, the normalized values of the overall index and subindices of HWB gradually increased from 2006 to 2012 (Appendix E: Table E1). Assigning reference scores of 0 and 100 to the individual communes with the worst

Table 1. Reliability tests of internal consistency for initial and refined designs, based on Cronbach's alpha value, ranging from 0 to 1, with higher values indicating higher internal consistency.

HWB dimension	Initial design	Refined design
Q1, basic material for good life	0.79	0.83
Q2, security	0.59	0.80
Q3, health	0.71	0.75
Q4, good social relations	0.67	0.69
Q5, freedom of choice and action	0.67	0.81

Notes: Detailed item–total correlations for each human well-being (HWB) dimension are shown in Appendix C: Tables C1–C5. The initial design is based on theoretic thinking (Appendix B: Tables B1–B5). The refined design is based on the combination of theoretic thinking and data maximization via structural equation modeling (SEM).

and best well-being statuses, respectively, the overall index across all communes improved from 63.28 to 72.86 (mean), and 66.17 to 75.86 (median) over the 2006–2012 period. There were 42% and 39% of communes with overall index values below average in 2006 and 2012, respectively.

For subindices, from 2006 to 2012, there were statistically significant increases in the average values of all five dimensions: basic material (86.53 to 88.85), security (63.12 to 72.20), health (14.48 to 22.96), social relations (90.53 to 94.44), and freedom (38.71 to 48.07). But the percentages of communes with subindex values below the corresponding average values were relatively stable from 2006 to 2012: basic material (30% to 32%), security (42% to 41%), health (56% to 53%), social relations (37% to 36%), and freedom (56% to 55%).

Trend analyses based on data across all the years (2006–2012) show that subindex values of basic material, security, health, social relations, and freedom increased at per-dimension rates varying from 0.47% to 9.34% per year from 2006 to 2012, respectively, altogether leading to an annual increase of 2.51% in the overall index (Table 3). Because the base values in 2006 for some indices (e.g., health, freedom of choice and action) are relatively low

Table 2. Summary of model-fit information for the structural equation model used to construct the HWB indices.

Fit statistic	Value
Chi-square (df = 412)	3361.523[***]
CFI (Comparative Fit Index)	0.959
TLI (Tucker-Lewis Index)	0.944
RMSEA (root mean square error of approximation)	0.025
SRMR (standardized root mean square residual)	0.026

Notes: We used the MLR estimator (maximum likelihood estimation with robust standard errors) in Mplus, with a scaled difference test (instead of the usual chi-square difference test method). We only included paths that are both theoretically meaningful and statistically significant. All included observed and latent variables were found to contribute to model fit significantly ($P < 0.05$). Missing values were removed and the total number of included observations is 11 361, for all years from 2006 to 2012. *** $P < 0.001$.

(Appendix E: Table E1), even a slight increase in the absolute value may actually lead to a big relative change across years.

Communes close to the Tonle Sap Lake and downstream Mekong River had higher HWB values than communes further away, where communes located in the north, northeast, and southwest of Cambodia had relatively low HWB values. These spatial patterns were highly significant, consistent over time ($P < 0.001$ in both 2006 and 2012; Table 4), and consistent across different HWB indices (Fig. 3).

Normalized index values present the relative changes in HWB over time and across space; however, they do not reflect the absolute status of HWB unless the non-normalized values of reference samples are provided. To resolve this issue, we presented the non-normalized values of reference communes (i.e., communes with highest, median, and lowest subindex values) using three sample indicators in each dimension (Fig. 4). In doing so, it could facilitate the interpretation of our results and potential cross-site comparisons.

Initial applications for testing external validity

To provide further quantitative evidence of external validity and demonstrate the potential applications of our method and indices, we attempted to examine some known relationships between HWB and some contextual factors in the Cambodia case (Table 4).

Globally, there is a trend that an improvement in HWB typically comes at the cost of degradation of natural capital (MA 2005, Raudsepp-Hearne et al. 2010). Developing countries are still in the early stage of the environmental Kuznets curve that predicts that their economies will grow while environmental pollution and degradation will increase (Stern 2004). Given that Cambodia is one of the least developed countries, we hypothesized that relatively more developed or urbanized communes should have higher HWB values, but more environmental pollution and degradation. Because relatively more developed communes are often where people converge at higher densities, we first used the total population, total number of families, and population density to examine their associations with our overall HWB indices in both 2006 and 2012. Our results show that overall HWB indices were significantly higher in more populous communes, with the associations between overall HWB index and total population, total number of families, and population density all positive and significant ($P < 0.001$; Table 4). We then used a road density indicator, for which we found consistent positive association as well. For the environmental pollution indicator, there was no significant association in 2006 but a positively significant association in 2012. In contrast, there was significantly lower HWB for communes containing protected areas and communes that had higher percentages of families living inside protect-

Table 3. Temporal trends of HWB indices from 2006 to 2012 based on regression lines.

Indices	Year	Constant	F	R^2	N
Subindex					
Basic material	0.410[***] (0.051)	−736.728[***] (101.968)	65.40[***]	0.006	11361
Security	1.503[***] (0.066)	−2951.167[***] (133.135)	514.37[***]	0.042	11361
Health	1.439[***] (0.039)	−2870.318[***] (79.190)	1331.95[***]	0.100	11361
Social relations	0.600[***] (0.026)	−1112.698[***] (51.914)	539.37[***]	0.047	11361
Freedom	1.573[***] (0.058)	−3116.642[***] (116.683)	733.62[***]	0.060	11361
Overall index	1.590[***] (0.067)	−3126.189[***] (134.069)	567.90[***]	0.047	11361

Notes: Dependent variables are HWB indices, respectively. Numbers outside and inside parentheses are coefficients and robust standard errors, respectively.
*** $P < 0.001$.

ed areas (Table 4).

In sum, these results all support our hypotheses and suggest evidence for strong external validity of our derived HWB indices. Nevertheless, it should be noted that such results only show the distribution pattern of HWB. We conducted these correlation analyses only to illustrate the external validity of our HWB indices. They do not suggest any causal relationships, which need further rigorous causal inference in future research. But based on our initial analyses and local knowledge of Cambodia, we may offer a qualitative explanation. The overall improvement of HWB indices in Cambodia between 2006 and 2012 was likely due to the economic development, particularly the extensive economic land concessions for industrial agriculture after 2005, which was concomitantly one of the major drivers for rapid deforestation in Cambodia during in the past decade.

Discussion

We propose a new method that uses structural equation modeling (SEM) to construct human well-being (HWB) indices for sustainability research and for policy planning and evaluation based on existing data sets. According to statistical analyses of internal consistency, temporal and spatial patterns, and initial applications, our proposed method and constructed HWB indices prove to be highly valid. Our method targets the use of second-hand data (including census data), which are widely available in many other places, although the spatial extent, temporal range, number of indicators, and analysis units (e.g., from household, village, and township to province and country) may vary from one to another. We believe that our method supports relatively easy replication elsewhere. In what follows, we discuss the advantages and limitations of our method and implications for future research and policy

Table 4. Bivariate regressions for sources of variation on overall HWB indices.

Indicator	HWB 2006	HWB 2012
Spatial pattern		
Nearest distance from centroid of each commune to Tonle Sap Lake (km)	−0.063[***] (0.006)	−0.055[***] (0.006)
Nearest distance from centroid of each commune to Mekong River (km)	−0.058[***] (0.004)	−0.042[***] (0.003)
Nearest distance from centroid of each commune to Tonle Sap Lake or Mekong River (km)	−0.191[***] (0.009)	−0.146[***] (0.008)
Demographic factors		
Total population of each commune (persons)	0.001265[***] (0.906×10^{-4})	0.0007498[***] (0.909×10^{-4})
Total number of families in each commune (family)	0.006592[***] (0.479×10^{-3})	0.003778[***] (0.442×10^{-3})
Population density, the number of people per unit area of each commune (persons/km^2)	0.000300[***] (6.770×10^{-4})	0.0001496[***] (4.090×10^{-4})
Development		
Road density, total length of roads per unit area of each commune (km/km^2)	0.150[***] (0.024)	0.071[***] (0.015)
Percentage of families who are affected by environmental pollution	10.397 (6.877)	14.288[*] (7.082)
Conservation		
Dummy variable: 1, communes contain protected areas; 0, communes do not contain protected areas	−11.058[***] (1.021)	−9.356[***] (0.959)
Percentage of families living in protected areas	−35.487[***] (3.194)	−31.819[***] (3.745)

Notes: The unit of analysis is the commune. Dependent variables are overall HWB indices in 2006 and 2012, respectively. The numbers of observations are 1561 and 1590 for years 2006 and 2012, respectively. Numbers outside and inside parentheses are coefficients and robust standard errors based on bivariate regressions, respectively.
* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$.

A) Overall HWB index

B) Subindex of basic material for good life

C) Subindex of security
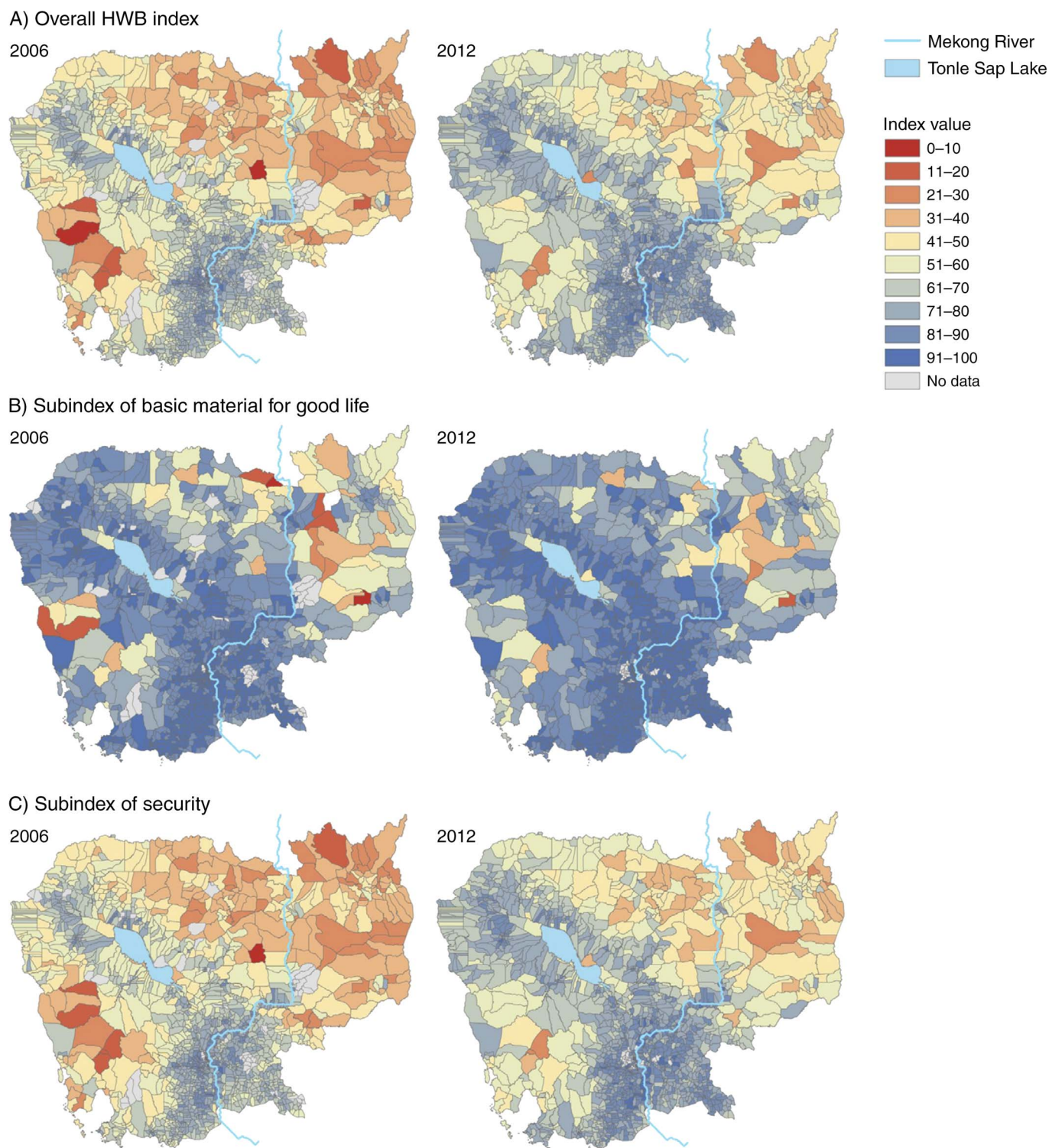
Fig. 3. Spatial dynamics of HWB indices in Cambodia from 2006 and 2012. Panel (A) represents overall indices in 2006 and 2012, while panels (B–F) refer to subindices in 2006 and 2012. A higher value indicates a better status. Comparison of indices across different dimensions is not appropriate as indices are constructed with different sets of indicators and normalized separately with different reference values. Figure continued on next page.

making.

There are some major advantages of our approach. First, it provides a pragmatic solution to construct HWB measures with high validity and maximum use of data

variation. The combination of theoretic design with data maximization through SEM resulted in indices that relate meaningfully to HWB dimensions and extract maximum use of data variation in each context. We
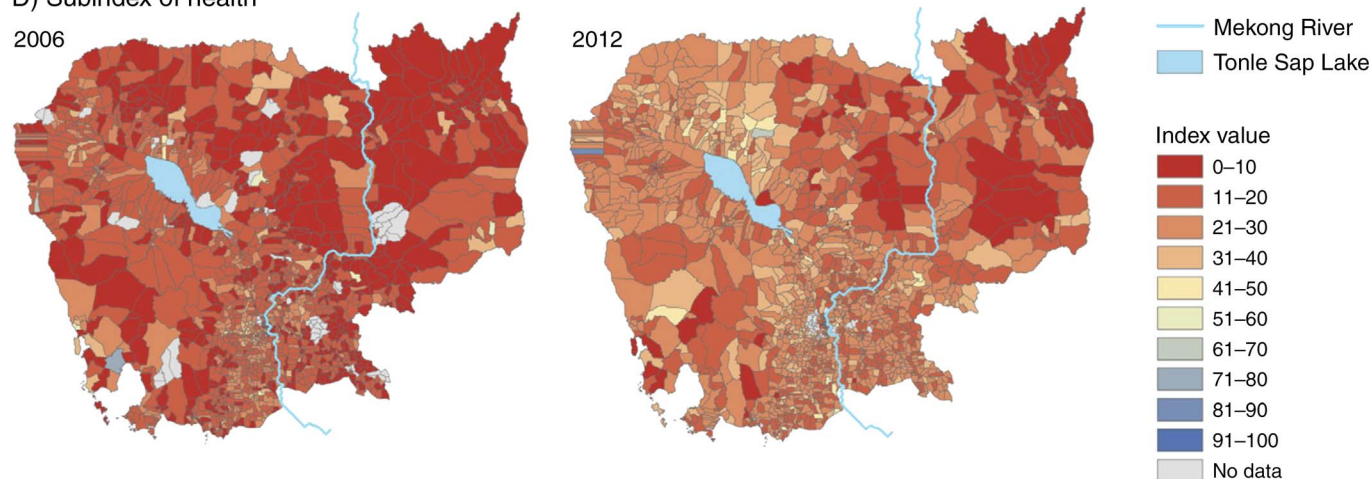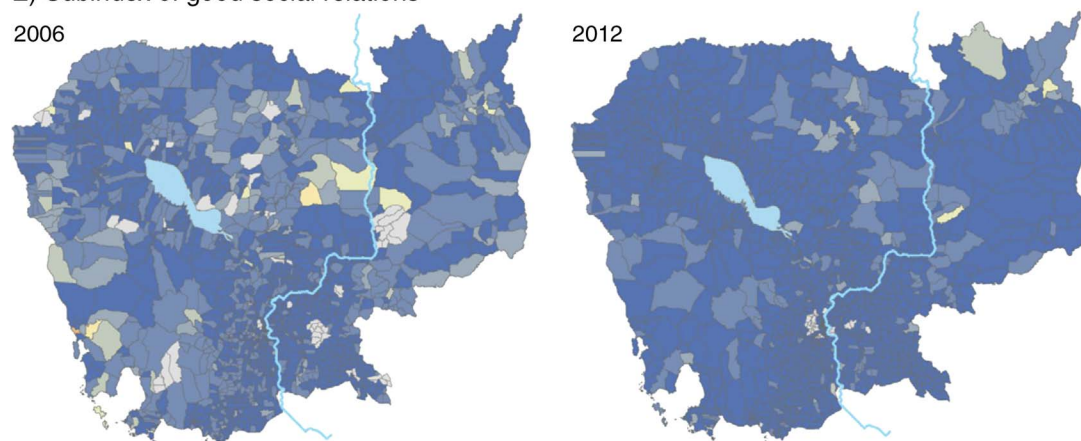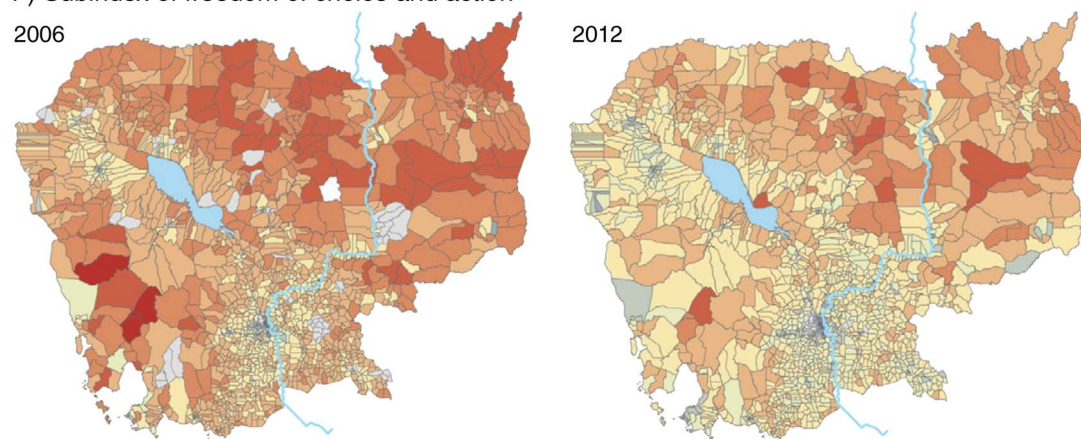
Fig. 3. Continued.

purposely demonstrated our method using a relatively poor data set in Cambodia, but certainly our method can be applied to places with better data. Second, the method is applicable to varied contexts and frameworks. Our method is scale-free and thus can be applied to different levels of analysis unit (e.g., from households, villages, communes, and counties to provinces and nations). Besides the MA framework used here, our approach could be easily modified and applied to other HWB frameworks by recategorizing the structural model in our structural equation model (Fig. 2). Third, the weighting of individual indicators and HWB
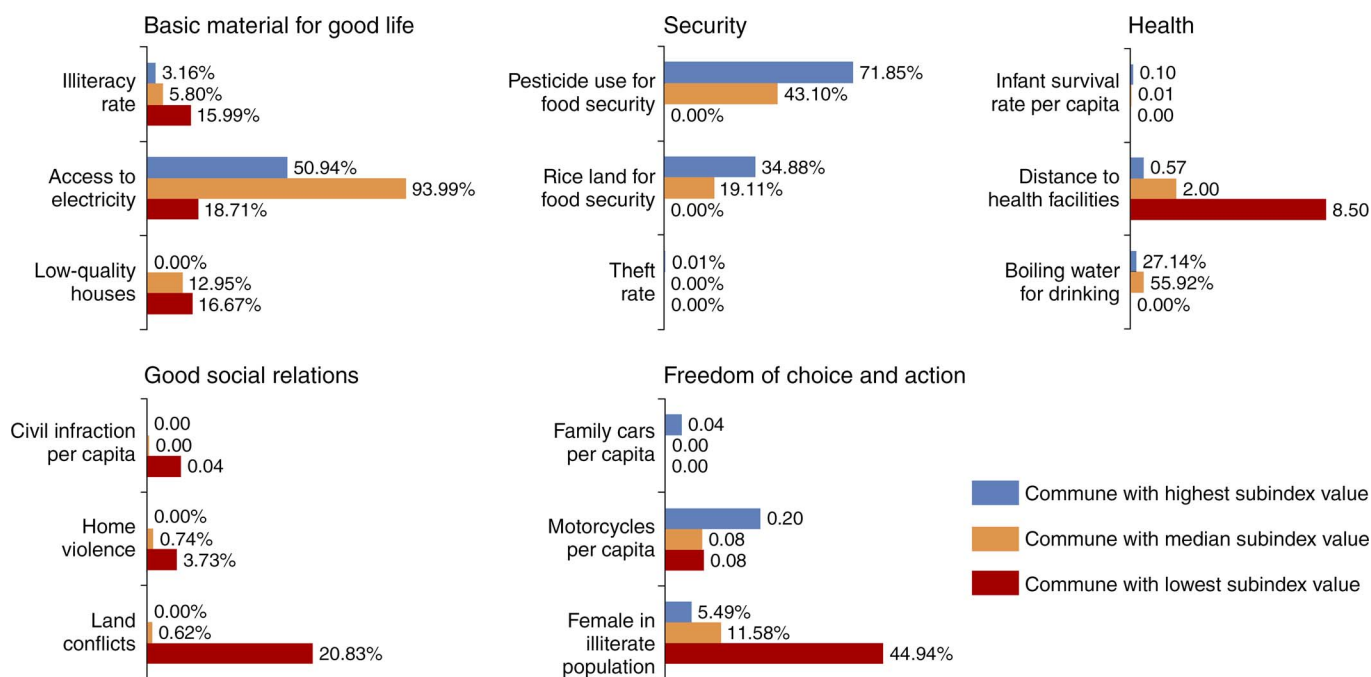
Fig. 4. Profiles of communes at different levels on the well-being subindex. This figure visualizes the characteristics of reference communes (i.e., communes that have the highest, median, and lowest values) with nonnormalized data (i.e., data in original units without minimum–maximum normalization) in each dimension, respectively. The three sample indicators for each dimension are displayed. Detailed descriptions of all indicators are provided in Appendix B: Tables B1–B5.

subindices from SEM are estimated simultaneously via embedded regression models based on data variation. They are neither assigned with equal weighting nor subjectively weighted by investigators. But if needed, equal weighting and subjective weighting by investigators are also allowed in SEM. Fourth, because SEM accounts for measurement errors of individual indicators in the measurement model, the derived indices from SEM are robust to measurement errors, while the direct use of individual indicators are not. Fifth, the approach, while requiring some specialist expertise to execute, is also relatively rapid to conduct, enabling researchers to respond to policy opportunities.

Finally, it is an index system consisting of not only the overall index but also subindices, which allow the display of overall temporal and spatial patterns in HWB, as well as disaggregated analyses in each dimension of HWB. The single-value overall composite index provides an easy measure of the overall status and is convenient for large comparative analyses, while it obscures some details and is less useful for understanding trade-offs and context-dependent mechanisms (Daw et al. 2011, Villamagna and Giesecke 2014). In contrast, individual disaggregated indicators, such as the selected 34 individual indicators from the Cambodia commune database, may lead to biased results, since each of them only covers a part of the full scope of HWB. The subindex of each HWB dimension from SEM allows us to greatly reduce the number of indicators and quantify HWB along meaningful dimensions, yet retain much of the detail of individual indicators. In practice, aggregated indices and individual disaggregated indicators may be used jointly for specific analyses to utilize the strengths of each and offset the limitations.

Our method and its applications have some limitations, primarily resulting from the secondary data themselves. The major limitations of the HWB indices are constraints presented by existing indicators. No composite index can infer properties of dimensions not represented in the underlying data. For instance, there are very few candidate indicators for social relations in the Cambodia Commune Database, and thus, there is limited potential to refine the subindex of social relations (Table 1). If certain components of HWB (e.g., mental health, social relation satisfaction, life satisfaction) were not measured or poorly measured in secondary data sets, the only remedy is to conduct complementary data collection (e.g., via additional surveys). Also, if the secondary data set is incomplete or not representative of the population being studied, this will also translate into incomplete or nonrepresentative HWB indices. In our case, for example, there are some "floating communes" consisting of groups of families living on boats in the Tonle Sap Lake. Although they are an important subgroup of Cambodia's population because they are particularly resource dependent and tend to be quite poor, they were not fully included in the commune database perhaps due to difficulty in data collection. Even with these limitations, our approach enables us to obtain maximum use of available

data, and by doing so, target limited survey resources to the topics and places where they are needed most.

Besides technical innovations, our method and developed HWB indices have broad implications for policy analysis and future research in the design, monitoring, and evaluation of policies and research on causal linkages between nature and HWB. Our HWB indices provide quantitative measures for identifying priority areas and vulnerable population groups for aid, monitoring poverty, and evaluating conservation and development interventions. For example, the Cambodian government announced its National Policy and Strategic Plan on Green Growth 2013–2030 (National Council on Green Growth 2013a, b), with an overall goal of improving the well-being of Cambodians. The policy emphasizes the multiple dimensions of well-being and its linkages to sustainable use of natural resources. Our organization has also been actively cooperating with the Cambodian government to ensure the successful implementation of this new national policy and inform approaches to monitoring and reporting on specific policy activities and outcomes. Our proposed HWB indices hold promise for supporting effective implementation and monitoring of this policy.

In addition, our method and HWB indices can be used for quantitative studies of linkages between nature and HWB. HWB indices are useful measures of vulnerability or resilience of human society in response to changes in provision of ES and adverse events as demonstrated in previous studies, such as assessing earthquake impacts and identifying vulnerable or resilient population groups (Yang et al. 2013a, 2015b). As we conduct further detailed assessment of ecosystems and ecosystem services in Cambodia, we intend to integrate these indices into quantitative causal inference analysis (Yang et al. 2013d, Ferraro and Hanauer 2014) to understand the impacts and mechanisms of policy interventions, such as protected areas, infrastructure construction, industrial agriculture, mining, and tourism development, on natural resources and on HWB in Cambodia. It is our hope that further refinement and application in other places could provide quantitative empirical evidence across different contexts in the short term and in the long run improve understanding of human–nature interactions and move toward robust theories of sustainability science.

Acknowledgments

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Supplemental Material

Ecological Archives

Appendices A–E are available online: http://dx.doi.org/10.1890/EHS15-0004.1.sm