Green infrastructure spatial planning

12 Novembre 2019 Scritto da silvia.ronchi il paper di Silvia Ronchi, Andrea Arcidiacono and Laura Pogliani á pubblicato sul Journal Sustainable Cities and Society Link al PAPER A growing number of cities are investing in green infrastructure to promote urban resilience and sustainability. While these nature-based solutions are often promoted on the basis of their multifunctionality, in practice, most studies and plans focus on a single benefit, such as stormwater management. This represents a missed opportunity to strategically establish green infrastructure to take advantage of social and ecological co-benefits. To address this gap, this document builds on existing modeling approaches to green infrastructure planning to create a more generalizable tool for comparing spatial offsets and synergistic hot spots for multiple desired benefits. I apply the model to three different coastal megacities: New York, Los Angeles (United States) and Manila (Philippines), allowing comparisons between cities for the first time. Spatial assessment of several criteria is used to examine how strategic areas for green infrastructure development change in all cities, depending on what benefit is prioritized. The GIS layers corresponding to six planning priorities (stormwater management, reduction of social vulnerability, increased access to green space, improvement of air quality, reduction of the effect of the urban heat island and increased landscape connectivity) are mapped and spatial compensations are evaluated. The criteria are also weighted to reflect the desired outcomes of local stakeholders as determined through surveys and stakeholder meetings and combined to identify areas of high priority for green infrastructure development. To extend the usefulness of the model as a decision support tool, an interactive web-based application is developed that allows any user to change the weights of the criteria and visualize the resulting access points in real time. The model empirically illustrates the complexities of green infrastructure planning in different urban contexts, while demonstrating a flexible approach to more participatory, strategic and multifunctional green infrastructure planning in cities around the world. Coastal megacities concentrate risks and resilience opportunities. On the one hand, densely populated urban areas are highly vulnerable to disasters and the impacts of climate change, while being responsible for much of the consumption energy consumption and carbon emissions (Klein et al 2003, Duren and Miller 2012). Urbanization in coastal areas also negatively affects the local environment, for example through sinking, pollution, habitat fragmentation and loss of ecosystem services (Blackburn and Pelling 2014). On the other hand, large cities can be part of the solution, presenting certain efficiencies and economies of scale (Seto et al 2010). There are numerous proposed strategies to mitigate impacts of urbanization and improving urban resilience, such as high albedo 'roofs and pavements', strategic buildings and street designs, and public transport (Coutts et al 2010). While previous studies have examined the relative merits of various strategies (see Georgescu et al 2014), it is worth looking more closely at green infrastructure because it is increasingly promoted in both research and practice (Mcphearson et al 2015, Finewood et al 2019). Definitions of green infrastructure vary, but generally refer to vegetated areas such as parks, greenways, rain gardens or green roofs (Koc et al 2017). A growing number of researchers, Government agencies and organizations are working to expand green infrastructure in cities around the world, and megacities are often leaders in environmental policies with significant economic resources for implementation (Parrish and Zhu 2009), however, how applicable and effective these approaches can be in mega-city contexts and how they can be implemented is an important area for experimentation and information sharing (Li et al 2015 , p 609). Green infrastructure is particularly attractive and widely defended because it is believed to provide a multitude of desired social, ecological and technical benefits, often called ecosystem services (Tzoulas et al 2007, Hansen et al 2019). Commonly cited benefits include improving stormwater management (Eckart et al 2017), improving water and air quality (Davis et al 2009, Pugh et al 2012, Wagner and Breil 2013), urban heat island mitigation (Norton et al 2015), improving physical and mental health (Amano et al 2018) , habitat improvements (Benedict and McMahon 2002), and increased property values (Netusil et al 2014). The ability of green infrastructure to provide multiple co-benefits can be especially important for coastal megacities, where there are many competitive demands for limited land (Von Glasow et al 2013). Despite numerous claims about the multifunctionality of green infrastructure, most studies and empirical plans focus on one or some of these benefits, especially stormwater and flood management (Venkataramanan et al 2019). Research on possible synergies and trade-offs between ecosystem services or green infrastructure functions is also limited (Lovell and Taylor 2013, Kremer et al 2016). In general, the impacts of green infrastructure are localized, so it matters how green infrastructure is distributed throughout the city (Hansen and Pauleit 2014, Heckert and Rosan 2018). However, efforts to strategically integrate different social and ecological planning of green infrastructure throughout the city have so far been limited, and there is a clear need for scientists to offer more practice-oriented tools and concepts to do so (Hansen et al 2019, p 108). Some of these tools have been developed for individual cities, which typically combine multiple GIS GIS to identify priority areas for green infrastructure (Madureira and Andresen 2013, Heckert and Rosan 2016, Kremer et al 2016, Sharma et al 2018). This article is based on one of these models, the Green Infrastructure Spatial Planning (GISP) model developed by Meerow and Newell (2017) and initially applied to Detroit, Michigan. Here not only do I increase the overallization of the approach by applying it to three coastal megacities (New York (NYC), Los Angeles (LA) and Metropolitan Manila (Manila)—but also improve its usefulness as a decision support tool by developing a web-based interactive application. The application of the model to three cities allows comparisons between cities and reveals a broader synergy of ecosystem services and compensation patterns. These three cities were selected based on several criteria. First, they are classified as coastal megacities, in the center of urban agglomerations with more than ten million residents and are located at 50 m altitude and 100 km of high middle water (Blackburn and Pelling 2014). In fact, NYC and LA are the only two U.S. cities classified as such. Second, all cities are vulnerable to multiple natural hazards (ONE DESA 2011, Sundermann et al 2013). Third, cities vary in terms of the scope of their green infrastructure planning. NYC is several years in the implementation of a comprehensive multimillion-dollar green infrastructure master plan (Kremer et al 2016). LA has several ambitious plans and programs, but all in the early stages. Metro Manila has only localized initiatives. An important motivation to include Manila in the study is to test the usefulness of the model outside the United States, in a relatively low data environment. From a practical perspective, American cities were selected due to accessibility, and the final selection of the three cities was made based on practical considerations associated with the stakeholder survey. I then outline the methodology used to develop the GIS model for the three cities, including mapping individual model criteria, evaluating synergy and compensation patterns, weighting stakeholders, and the web-based tool. I present the results and then analyze the implications of these findings, the important limitations of the model and possible future extensions. The GISP model provides a general approach to mapping priority areas where green infrastructure can be strategically placed to maximize the benefits of ecosystem services and assess spatial offsets (Meerow and Newell 2017). The model combines multicritical evaluation GIS and the weights derived from stakeholders. The six criteria, which represent the commonly cited benefits of green infrastructure, include: (1) stormwater management; 2) reduce social vulnerability; 3) increase access to green space; (4) reduce the urban heat island (UHI); 5) improve air quality; and (6) increasing the landscape or habitat habitat These are combined and weighted according to the planning priorities of local expert stakeholders. This document improves the initial model by updating data sources, comparing findings in three very different cities, and developing a new interactive web-based tool. Allocation criteriaSo possible, similar datasets were used for all three cities, but especially for Manila, this was not always possible. This limitation is discussed further in the debate. For each of the six criteria, indicators are added to the smallest spatial unit for which they were easily available to the data. For New York City and LOS which is the 2010 census tract, and for Manila the barangay or village (the smallest local census and government unit). Official census boundaries were cut to include only land areas. Since some indicators consider the population, populationless districts (e.g. parks, water characteristics) were excluded from the analysis. The model is built from widely available spatial datasets selected in consultation with local experts. The data for each criterion was processed and assigned separately; with a linear scale transformation ('maximum score'—see Appendix A in the supplementary material is available online in stacks.iop.org/ERL/14/125011/mmedia for equation) applied to measurement scales so that all criterion scores were standardized to range from zero to one (Malczewski 1999). The selection justification for each indicator, data sources, and processing steps are described below and summarized in Table 1.Table 1. GIS model criteria and data sources for all three megacities. Resilience Planning Priority Criterion Spatial Attributes (Indicator) Los Angeles Data Source New York City Data Source Manila Data Source Stormwater Hazard Management Percentage Waterproof Surface Waterproof Surface Dataset NASA Global High Resolution Urban Data SEDACs Global High Resolution Urban Data Global (2010) Waterproof Surface Dataset (2010) SEDACs Global High Resolution Urban Data from Landsat Collection Global Man-made Impervious Surface Dataset (2010) by NASA SEDACs Global High Resolution Urban Data from Landsat Collection Reducing social social Man-made Impervious Surface Dataset (2010) NASA SEDACs Global High Resolution Urban Data from Landsat Collection Social Reducing Social Vulnerability Index Social Vulnerability Index (SoVI) Combination of indicators associated with social vulnerability to natural hazards SoVI Data for 2010 created by Instituto de Investigación de Peligros y Vulnerabilidad (2015) SoVIY Research Institute (2015) SoVI data for 2010 calculated for cities in Metro Manila by See and Porio (2015) Increasing access to green space Lack of access to parks Park access indicator Population weighted distance to nearest park from buildings within tract based on on on on on on on on on on on on on on on on on on on on Open Street Map (Logan et al 2019) Distancia ponderada de población al parque más cercano desde edificios dentro del tracto basado en Open Street Map (Logan et al 2019) Distancia media hasta el más cercano cercano inside barangay based on Open Street Map (Logan et al 2019) Reduction of the urban heat island effect Earth surface temperature Average earth surface temperature for three months estimated LST using landsat 8 infrared thermal bands, near infrared and red. LST estimated using thermal bands of infrared, near infrared and red Landsat 8. LST estimated using thermal bands of infrared, near infrared and red Landsat 8. Improved air quality Severity of air pollution Severity Of air pollution Total cancer risk by the National Air Toxics Assessment (U.S. Environmental Protection Agency 2018) Total cancer risk by National Air Toxic Assessment (U.S. Environmental Protection Agency 2018) Percentage of total area within 200 m of a major highway. (University of the Philippines School of Urban and Regional Planning 2013) Increased landscape connectivity Physical connection of wildlife habitat (vegetated areas) patch cohesion index (Fragstats) Physical connection of the canopy of trees (LA Regional Imagery Acquisition Consortium LAR-IAC 2011) Vegetated physical connection zones (excluding built and water areas) based on ECM (O'Neil-Dunne et al 2014). Physical connection of wildlife habitat (excluding constructed and water areas) using NAMRIA land cover data (2010) Stormwater ManagementTo identify priority areas for green infrastructure based on stormwater management, estimates of the percentage waterproof surface (IP) for each space unit were calculated. Waterproof surfaces, such as buildings, roads and pavement, prevent water from infiltrating the ground and are therefore more likely to lead to runoff that collects contaminants, phases in sewer infrastructure and potentially causes flooding (Shuster et al 2005). IP datasets were purchased for each city from NASA's Center for Applications and Socioeconomic Data. The man-made Global Waterproof Surface Data Set (GMIS) is a product made from Landsat 2010 data with a spatial resolution of 30 m (Brown de Colstoun et al 2017). Reducing social vulnerabilityThe green infrastructure has been linked to numerous social and community benefits, so it may be strategic to place new developments in disadvantaged or socially vulnerable communities. There are many possible indicators of social vulnerability, possibly the most well established being the Social Vulnerability Index (SoVI) (Cutter et al 2003, Cutter and Finch 2008). For LA and NYC, SoVIs were calculated for cities by researchers from the Institute for Hazard and Vulnerability Research using 27 variables from the 2010 Census and the 2006-2010 American Community Survey for all census tracts. For NYC, the index had 7 factors representing 70% of the variance, and LA had six representing 68%. No SoVI has been calculated at the barangay level for Manila, but See and Porio (2015) have created a SoVI based on 2010 census data for each of the 16 cities and a municipality that make up Metropolitan Manila. Without any additional data for barangays, I had to simply assign each barangay the SoVI value of the city in which it is located, although this is likely to darken the intra-urban variation given the high income inequality of the Philippines (UN-Habitat 2013). Increased access to green spaceManuquíes have shown that green spaces are not evenly distributed among cities, which is problematic given their many benefits (Wolch et al 2005, Nesbitt et al 2019). New investments in green infrastructure could be made in communities with less access to green space to cope with this inequity. To identify these areas in New York and La, I used an indicator that represents the weighted average distance of the population to the nearest park for all buildings within a census tract (Logan et al 2019). The Logan et al model uses open source data from OpenStreetMap (OSM) and the open source routing machine (OSRM; to calculate the walking distance between each building (using the footprint data of the city building) and the nearest park (OSM). The total population of the census block (from the 2016 U.S. Census TIGER/Line Shapefiles) is evenly divided among the buildings in that block. This indicator is calculated by multiplying the population and distance of the park assigned to each building, adding these values for the tract, and dividing this by the total population of the tract. In Manila, this approach was modified because no building footprint or population dataset could be identified. A grid of 100 m of origin points overlapned through Manila, the distance from each origin to the boundary point of the calculated nearest park, and the average distance determined for all points of origin within each barangay. This indicator is significantly different from that used in NEW York and LA, as it is not population weighted. Reducing the UHI effectThe reception can cool the local environment, thus helping to mitigate the UHI (O'Neill et al 2009). As an indicator of UHI in each city, I used terrestrial surface temperature (LST) datasets calculated from the Landsat 8 thermal infrared sensor using the method based on radiative transfer equations (Yu et al 2014). Landsat scenes were identified based on three criteria: (1) less than 10% terrestrial cloud coverage, (2) as close as possible to the summer months of the region, (3) the most recent scene available to the study area. On June 12, 2017, it was used for New York City, July 11, 2017 for Los Angeles, and February 13, 2016 for Manila. Manila had few scenes without coverage Clouds. While LST is widely used as a UHI indicator due to its availability, surface temperatures may not reflect the temperatures people experience as well as air temperatures, although both are generally correlated (Well 2016). Improving air qualityVegetation can reduce air pollution, such as particulate matter and ozone (Pugh et al 2012). Identify high-priority areas for quality improvement in New York and LA, I used the U.S. EPA's 2011 National Air Toxic Assessment. The EPA produces this model of respiratory risk screening for human health from outdoor air toxics on a census tract scale, which are designed to identify geographic patterns and risk ranges (U.S. Environmental Protection Agency 2018). Although this data has many limitations, it is freely available throughout the United States (Chakraborty et al 2017). I used total cancer risk estimates for each tract. Unfortunately, no barangay-level air quality models could be identified for Manila. Transport-related emissions are among the most harmful to public health, and concentrations of air pollutants are closer to major roads (Design for Health 2007). Therefore, I used proximity to major roads as a proxy for critical air pollution points. I calculated a 200-meter mattress (the threshold used by the U.S. Department of Transportation for proximity to major roads) around all roads with more than four lanes, and then calculated the percentage of each total barangay area within the buffer. Increased landscape connectivityVegetation and green spaces provide shelter and resources for many species, but this remaining habitat is fragmented into urban areas, resulting in fewer ecosystem services (Mitchell et al 2013). One possible solution is to connect and expand the remaining green spaces, and research suggests that these networks can provide valuable habitat (Kong et al 2010, Zhang et al 2019). Fragstats is a free and easy-to-use software program for horizontal connectivity calculations (McGarigal et al 2012). Within Fragstats, the patch cohesion index provides a measure of the physical connection of habitat patches across a landscape. I calculated the patch cohesion index for the plant coverage of each spatial unit in each city, assuming that these areas would provide habitat to several species. This makes the results subject to edge effects, as each tract is analyzed in isolation. In New York, I used the high-resolution ecological covertype map (O'Neil-Dunne et al 2014) and the combined areas classified as 'forested wetlands', 'freshwater wet', 'maintained grass and shrubs', 'sea forest', 'other canopy of trees',

'tidal wetlands', 'highland forest', and 'highland shrubs and shrubs' in habitat patches. In LA I it used canopy areas of trees as habitat patches (LAR-IAC 2011), and because much of the dataset Manila land (NAMRIA 2010) was classified as 'built' I included all areas classified as 'mangrove forest', 'open forest', 'broadleaved', 'annual and perennial crops', 'sterile land, meadows, marshes' and forested lands (shrubs, wooded grasslands) as habitat patches. Determining stakeholder priorities and criteria weightsIn addition to the allocation of the six criteria, I carried out fieldwork in each of the three cities and and stakeholder meetings (LA in February 2016, Manila in August 2016 and NYC in January 2017) that brought together local experts and decision makers for green infrastructure planning. At all three events, I presented the model and asked participants to complete a survey comparing the relative importance of the six model criteria using three different methods: classification, classification and peer comparisons (for more details, see Appendices B and C in the supplementary material). Although not representative, the survey aims to gather a number of expert opinions in each city to give some indication of the relative importance of the criteria. The results of the peer comparison survey questions were added to produce weights. Peer comparison analysis was performed using the Excel-based AHP calculator (Goepel 2013) or the AHP Survey package (Cho 2019). Then I used the weighted linear combination to develop combined hotspot maps for green infrastructure expansion. Interactive web-based toolRecognizing that survey results may not be representative and that priorities may change over time, I also created a web-based tool that allows users to adjust weights and immediately visualize combined and weighted results (www.gispmodel.com; Meerow 2019). The tool was developed using R Shiny Applications (Chang et al 2019) and a tool-like structure designed for conservation planning (Coristine et al 2018). The development of the GISP model for three different megacities highlights the complexities of green infrastructure planning to maximize multiple resilience benefits. Priority areas for green infrastructure differ clearly depending on the decision-making criteria. Some patterns of synergy and spatial compensation are consistent in all three cities, while others differ. Local priorities also seem to vary between the three cities, confirming the need to consult stakeholders and customize weighting schemes. The six individual criteria maps for each of the cities are shown in Figures 1–3. In each case, darker shaded spatial units represent areas that are of higher priority for model-based green infrastructure development. It is clear that spatial priorities vary by criteria. I examine these compensation and synergy relationships quantitatively by executing Pearson's bivariant correlations between the criteria in each city (Figure 4). Figure 1. Green Infrastructure Spatial Planning Model Criteria New York. Note: Each map shows the relative prioritization of census tracts in New York for green infrastructure based on the commonly cited benefits of green infrastructure. Download figure: Standard image High resolution image Figure 2. Criteria of the Green Infrastructure Spatial Planning (GISP) model, for your data). Note: Each map shows the relative prioritization of census tracts in Los Angeles for green infrastructure based on the commonly cited benefits of Figure: Standard Image High Resolution Image Figure 3. Criteria for the Manila Green Infrastructure Spatial Planning (GISP) model. Note: Each map shows the relative prioritization of barangays in Manila for green infrastructure based on the commonly cited benefits of green infrastructure. Download figure: Standard image High resolution image Figure 4. Spatial compensations and synergies between GISP model criteria. Note: The larger the diameter and shading of the circles, represent the Pearson correlation coefficient for the GIS model criteria. A larger circle indicates a stronger negative (red) or positive (blue) ratio. Circles marked with an 'X' are not statistically significant. Download figure: Standard image High resolution image Analyze spatial synergies and offsetsCorrelations between criteria scores (Figure 4) reveals possible spatial offsets and synergies between planning priorities. A positive correlation indicates spatial synergy, while a negative relationship indicates compensation. Certain correlation patterns are consistent in all three cities. I find a positive correlation (synergy) between the stormwater, air quality and UHI criteria, and a balance between these three criteria and the connectivity criterion. This is not surprising as areas with more connected vegetated areas should have less impervious areas, reduce air pollution levels and be cooler. The IP surface is often used as a UHI indicator, so we would expect the stormwater criterion and UHI criterion to correlate (Yuan and Bauer 2007). Other relationships are not consistent in all cities. Stormwater and social vulnerability are positively correlated in Los Angeles and Manila, but not in New York. In both New York City and LA, there seems to be a balance between access to green space and air quality. In New York, I also find weak evidence for a balance between access to green space and LA UHI. This may be because densely populated Manhattan is built around Central Park, which puts most residents there very close to green space. While there is some evidence of a synergy between SoVI and UHI in Manila and to a lesser extent LA, we see a negative correlation in New York. Deeper field research and a more detailed study of specific neighborhoods in each of these cities are likely to be needed to understand these differences. In general, the results suggest that it may be possible to locate green infrastructure in high priority areas for stormwater management, air quality and UHI simultaneously. Trying to socially vulnerable neighborhoods, those with less access to parks, or expanding and connecting existing habitat can be more problematic. The existence of these trade-offs suggests that decision-makers should assess local priorities as part of a strategic planning process. Local priorities and mapping of green infrastructure hotspotsExpert stakeholders in the three cities seem to have with respect to the benefits of green infrastructure. Table 2 presents the aggregated results of the survey of the importance of model criteria for each city. Interestingly, the order is only completely consistent across the entire rating, ranking, and peer comparison questions for LA, and this is the city with the fewest respondents. However, there still appears to be some consistent prioritization patterns in New York and Manila. This becomes apparent when you look more closely at the means (for the grading question a higher score indicates that a criterion is considered more important, while for the ranking question a lower score means that a criterion is more important) and the weights (higher is more important) generated from the peer comparison question. For example, in New York City, stormwater management is identified as much more important than the other criteria, which are very close by. In Manila, the benefits of stormwater and air quality received almost the same priority. Table 2. Stakeholder Survey Results: Aggregated stakeholder survey responses in each city for questions that ask them to individually rate, classify, and compare (using peer comparisons) the importance of the six GISP model criteria for the location of green infrastructure. Note: 'Classification order' reflects the ordinal importance of the criteria (1 is the most important). New York City (N to 28) Los Angeles (N to 6) Manila (N - 19) Classification Order Average Standard Deviation Order Classification Order Average Standard Deviation Order Standard Classification Question Standard Deviation Rating Question Stormwater 1 4.71 0.66 2 4.50 0.55 2 4.53 0.84 Sovi 3 4.18 1.16 1 4.83 0.41 3 4.21 0.092 Green space 5 4.07 0.86 3 4.00 0.63 4 4.11 0.74 UHI 4 4.14 0.76 4 3.83 0.41 5 4.05 0.91 Quality air 2 4.29 0.76 5 3.67 1.03 1 4.58 0.51 Connectivity 6 3.86 0.93 6 3.50 1.5105 5 4.05 1.08 Sort order Classification order Average standard deviation Standard classification order Standard classification order Standard deviation order Storm 1 1.71 1.33 2 1.67 0.82 1 2 .55 1.75 Sovi 2 3.25 1.80 1 1.50 0.55 5 54.00 1.41 Green space 4 3.75 1.55 3 3.67 0.82 3 3.82 1.54 UHI 5 3.93 1.15 4.17 1.47 4 3.45 2.02 Air quality 3 3.54 1.43 5 4.50 1.05 2 2.45 1.13 Connectivity 6 4.82 1.39 6 5.50 0.84 6 4.60 1.51 Peer Comparison Question Sort Order Order Range Weight Order Weight Weight Stormwater Weight 1o0.295 2 0.277 1 0.227 Sovi 3 0.166 1 0.337 4 0.168 Green Space 5 0. 122 3 0.125 3 0.169 UHI 2 0.171 4 0.099 5 0.120 Air quality 4 0.1485 0.097 2 0.211 Connectivity 6 0.096 6 0.064 6 0.105 Consistent with other studies (Newell et al , Meerow and Newell 2017), stormwater was considered one of the most important benefits in all three cities. The other benefits varied. This may be because green infrastructure has been specifically promoted by institutions such as the U.S. EPA as a stormwater management approach. NYC's green infrastructure plan, for example, sets specific targets related to improving water quality and runoff management, while the other desired sustainability benefits are not as well defined (PLANYC 2010, p 2). Reducing social vulnerability was considered more important in LOS, but a little less so in New York and Manila. The benefits of air quality were seen as very important in Manila, but not in New York or La. Increased landscape connectivity was seen as one of the least important criteria, perhaps suggesting that stakeholders are more interested in social benefits than in the more indirect ecological services of green infrastructure. Figure 6 shows critical points for green infrastructure when weighted and combined criteria (for comparison, combined results without stakeholder weights are presented in Appendix D of the supplementary material). We can see, for example, areas of high need for green infrastructure in the Bronx and queens and Brooklyn around Newtown Creek in New York, in the southeastern and central part of LOS, and in some of the oldest and densely populated Western neighborhoods of the city of Manila (see these areas highlighted in Appendix E in the supplementary material). Standard deviations in survey responses (table 2) show that priorities differ, and this survey represents a single snapshot in time and a limited sample. In contrast, the web-based tool (Figure 6) allows anyone to enter their own weights on a scale of one to ten using sliders for each of the six criteria and then press a button to immediately display the combined and weighted responses on a street, antenna, or terrain map. Users can zoom in on particular areas of interest and switch between different criteria layers or combined results. This allows for greater flexibility and encourages exploration of data and scenarios. New York, La and Manila represent three very different coastal megacities. However, in all three cities there are ongoing efforts to expand green infrastructure and urban vegetation to improve sustainability and resilience. This is part of a broader trend, as an increasing number of academics, organizations and governments are promoting the multiple benefits of green infrastructure (Prudencio and Null 2018, Hansen et al 2019). The GISP model was developed as a city-wide approach to strategically plan investments in green infrastructure based on where multiple benefits are most needed, and helps discover potential patterns of synergy and spatial balance between planning priorities (Meerow and Newell 2017). Extending the GISP model for the first time to compare cities reveals a number of interesting findings. First, it shows that it is possible to develop the model for very different cities, although it was much more difficult to acquire data on a sufficiently fine scale for Manila, and the results results be interpreted with caution. Second, while different data sources were used for cities, there are several consistent synergy and compensation guidelines (Figure 4). I identify spatial synergies between stormwater benefit criteria, UHI and air quality, and a balance between these criteria and increased landscape connectivity. The same thing happened in detroit's initial model (Meerow and Newell 2017). This is promising, because it suggests that even if stormwater remains an important focus of green infrastructure investments, and if high-impermeaciated areas are prioritized, developments can also help address UHI problems and air pollution. By contrast, stormwater-focused planning would not necessarily capture areas of relative park poverty, for example, although increased access to green space was seen as an important goal in all three cities. Similarly, stakeholder surveys indicated that stormwater and social vulnerability were important criteria for the location of green infrastructure in New York and LA, so it is potentially problematic that the two criteria were not positively correlated in New York, and only weakly in LOS. Third, the results of the survey suggest that expert stakeholders consider certain green infrastructure benefits to be more important in some cities than in others (Table 2). However, comparisons should be made with caution, as the number and institutional affiliation of respondents is very different in all three cities (Appendix C in the supplementary material). While the stakeholders I interviewed and amended for this study saw a practical value in the GISP modeling approach, there are some limitations. First, the model is constrained by data availability. It was difficult to find comparable datasets for all three cities, especially Manila. For example, access to green space and air quality indicators used for Manila is different from those used for LA and NYC. Differences in data used for the Manila model, combined with the fact that Manila, and the Philippines in general, is very different from LA or NYC in the United States, limits the comparative claims that can be made about compensation and synergy patterns in all three cities. Temporary inconsistencies in different datasets (e.g. 2010 SoVI vs. LST 2016/2017 data) can also influence compensation or synergy patterns within cities. The accuracy of the model depends on the underlying datasets, which are likely to Imperfect. I also acquired data from a wide variety of sources, making it difficult to validation of its accuracy. Ultimately, there is a balance between using data-driven indicators that are widely available and easily replicated compared to data that is highly customized and grounded. The analysis unit (the census tract and barangay) also limit the usefulness of the model. While census tracts are commonly used in studies (such as each tract represents an average of 4000 residents, so there is likely to be variability within them. In addition, census tracts are not related to the scales on which governance or planning occurs. Barangays represent the smallest local government unit in the Philippines, but their population varies even more than U.S. census tracts, the largest in Manila having nearly 250,000 residents (Philippine Statistics Authority 2016). Despite these limitations, the GISP model, in particular the new web-based tool (Figure 6), has the potential to report on more strategic spatial planning of green infrastructure to improve social and ecological resilience. New York and LA already have ambitious plans to expand green infrastructure with explicit multifunctional goals, and Manila is developing rapidly and is looking for ways to do so in a greener and more resilient way. To maximize limited investment in green infrastructure, these cities could focus on the neighborhoods identified by the model as high priority (Figure 5). Decision makers can also use the web-based tool (Figure 6) to explore in real time how prioritizing different criteria changes priority neighborhoods and identify potential critical points across the city for the set of green infrastructure benefits they consider most important. The GISP model could be used as an initial step in developing a city-wide green infrastructure vision plan or identifying areas for detailed suitability assessments. These finer-scale analyses would identify specific sites within priority areas modeled for green infrastructure development, as well as appropriate technologies and designs based on land use, costs, and other important contextual factors (Georgescu et al 2015). Figure 5. Access points for the green infrastructure location in New York, Los Angeles, and Manila: six criteria combined and weighted using peer-to-peer comparison survey results. Download figure: Standard image High resolution image Figure 6. Screenshots of web-based tools for the three cities (www.gispmodel.com). Download Figure: Standard Image High Resolution Image Finally, the flexible modeling approach could be applied to virtually any city in the world that is investing in multifunctional green spaces, helping them plan more strategically for the desired results locally. Many of the datasets used here are widely available (e.g. images detected Open Street Map). Different model criteria and specific indicators (e.g. air temperature or air quality monitoring data) could also be replaced or added to refine the accuracy of the results and adjust the model to the unique social or geophysical contexts of cities. Future applications of the model to other cities can also further validate the generalization of the synergy of ecosystem services and the compensation patterns identified in this document. Many people helped with this study. I'd like to thank Richard Schuster for help in the development of the original R Shiny app, and Srinivas Vallabhaneni for additional assistance. 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Data supporting the results of this study are openly available at . .