THESIS

EVALUATING THE UTILITY OF GLOBAL VERSUS LOCAL GEOSPATIAL DATA FOR SECONDARY CITIES

Submitted by

Danielle Brooke Davis

Department of Ecosystem Science and Sustainability

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Master's Committee:

Advisor: Melinda Laituri

Beth Tulanowski
Kathleen Galvin

ABSTRACT

EVALUATING THE UTILITY OF GLOBAL VERSUS LOCAL GEOSPATIAL DATA FOR SECONDARY CITIES

The 21st century is experiencing the emergence of the world's secondary cities as major urban growth areas. Secondary cities are regional hubs for commerce, logistics, services, and governance. They have populations ranging from under 300,000 to 5 million and are experiencing rapid, unplanned and informal growth patterns. Their dynamic growth means secondary cities are often data-poor and under-resourced, which impacts the ability of governments to target development efforts, respond to emergencies, and design sustainable futures. This research is a result of the Secondary Cities (2C) Initiative of the U.S. Department of State, Office of the Geographer and Global Issue. This initiative utilizes field-based participatory mapping for data generation to help secondary cities prepare for resilience, human security, and emergency preparedness. Geospatial data are key to the sustainable development of secondary cities for the future. Given the importance of geospatial data I explore two types of geospatial data for informed city planning: globally available data and locally collected data. First, I examine globally available data by assessing Sustainable Development Goal (SDG) Indicator 11.3.1, which compares land consumption rate to population growth rate, utilizing the recommended data. I apply SDG Indicator 11.3.1 to five 2C cities: Denpasar, Indonesia; Esmeraldas, Ecuador; Kharkiv, Ukraine; Medellín, Colombia; and Mekelle, Ethiopia. Second, I examine locally collected geospatial data of urban springs data collected in Kharkiv, Ukraine as a potable water source during a case of emergency. Specifically, these examinations utilize

suitable data that are products of the 2C Initiative. The results revealed unexpected nuances of both data types that proved complimentary to each other.

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PREFACE

The 21st century is experiencing the emergence of the world's secondary cities as major urbanizing areas. Secondary cities function as regional hubs for commerce, logistics, services, and governance, which affect urban resilience and sustainability. They are experiencing rapid, unplanned and informal growth patterns. This dynamic growth means secondary cities are often data-poor and under-resourced, which impacts the ability of governments to target development efforts, respond to emergencies, and design sustainable futures. The Secondary City (2C) Initiative is a field-based initiative of the Office of the Geographer, U.S. Department of State. Beginning in 2015, the 2C Initiative maps secondary cities to address resilience, human security, and emergency preparedness. The project builds local to global and public-private partnerships to create geospatial capacity, enhance data generation, local mapping, and enable science-based decision making about urban environments. Research for this thesis focuses on the advantages and limitations of globally available data and locally collected data for informed city planning and development in secondary cities case studies.

Chapter 1 is an introduction outlining the need to focus on Secondary cities, the role of geospatial data for these cities, and introduces the difference between globally available data versus locally collected data.

Chapter 2 is a methods chapter that reviews the practicality of recommended globally available data for Sustainable Development Goal (SDG) Indicator 11.3.1 that compares land consumption to population growth rate. We completed SDG Indicator 11.3.1 on five 2C Initiative cities: Denpasar, Indonesia; Esmeraldas, Ecuador; Kharkiv, Ukraine; Medellín, Colombia; and Mekelle, Ethiopia. The recommended globally available data are suggested in the United Nations Human Settlements Programme (UN HABITAT) *Guide to Assist National and*

Local Governments to Monitor and Report on SDG 11+ Indicators. Appendices A thru C are specific to SDG Indicator 11.3.1 completed on cities in chapter 2.

Chapter 3 examines how locally collected data in Kharkiv, Ukraine is used for city emergency preparedness. Data on population nearest each urban spring is compared to the amount of discharge each spring supplies. Results from analysis display the amount of population in Kharkiv that can be supported by the urban springs during an emergency. Assessment of the amount of population that can, and cannot, be supported by urban springs leads to recommendations for district administrators about water sources for citizens in case of emergency. Appendix D includes photographs of a sample of the urban springs in Kharkiv.

The thesis concludes in Chapter 4 with conclusions and reflections of globally available data and locally collected data used in this thesis. In addition, I reflect on the possible benefits and implications for all globally available data and locally collected data.

CHAPTER 1

INTRODUCTION

Introduction

Megacities have historically been the primary urban areas of growth. However, the 21st century is experiencing the emergence of the world's middle-sized cities, or secondary cities, as major growth areas especially in low and middle-income countries (LMICs) (Roberts, 2014; UN-HABITAT, 2016b). Sustainable development is increasingly dependent on the management of urban growth (Angel, 2012). In the developing world, there are a number of issues cities face with increasing growth, such as environmental degradation, citizen safety fears, and economic growth impediments. In particular, secondary cities are where most growth is occurring and yet receives little attention on the global stage (Angel, 2012).

A secondary city is defined by population, size, function, economic status, and the neighboring and/or distant cities and their socio-economic status within the country they reside. Secondary cities are urban centers providing critical support functions for governance, transportation, and production services for their country, however, lack attention on the global stage (Angel, 2012). Regardless, common characteristics include rapid unplanned and informal growth patterns (Roberts, 2014). Secondary cities in LMICs experience a number of issues due to their dynamic growth, such as environmental degradation, citizen safety fears, and economic growth barriers (UN-HABITAT, 2016b). This creates a host of environmental security and sustainability issues that impacts the ability of governments to implement development efforts, respond to emergencies, and design sustainable futures. Unfortunately, their dynamic growth and lack of visibility on the global stage means secondary cities are often data-poor, under-resourced, and lag behind in infrastructure and essential services (UN-HABITAT, 2016b).

The Secondary City (2C) Initiative is a field-based initiative of the Office of the Geographer, U.S. Department of State. Beginning in 2015, the 2C Initiative maps secondary cities to address resilience, human security, and emergency preparedness. From 2015 - 2019, the 2C Initiative implemented 16 projects located on five continents; six projects in Latin America, five projects in Eastern Europe and Asia, and five projects in Africa. The project builds local to global and public-private partnerships to create geospatial capacity, enhance data generation, map locally, and enable science-based decision making about urban environments.

Secondary cities need geospatial methods for data collection, mapping, and analysis to better understand urban areas and growth for planning. The 2C Initiative addresses the need for data collection and geospatial analysis of cities in LMICs. Partnering with local governments, non-governmental agencies, and universities, the 2C Initiative targets data generation to map urban form, but also to train the next generation of geospatial land use experts.

Geospatial technologies are key to helping sustainable development for secondary cities in LMICs. In this paper, I examine the use of globally available data and locally collected data for secondary cities. Global data have many benefits; unfortunately, the advances of global data have several limitations. Global data obscures local patterns due to the spatial scale and coarse resolution. Access to global data from web portals can be time consuming and confusing due to a lack of adequate tutorials, need for preprocessing of data for analysis, and issues with downloading corrupt datasets. Requests for help from global data providers often take days, weeks, or months depending on how many employees are dedicated to troubleshooting and interfacing with data users. Algorithms that create the global data are useful at large scales, however, often misrepresent smaller scales, such as secondary cities (Martino Pesaresi et al., 2013). Based on literature, I define globally available data as global data that is *spatial,* publicly available, and has global coverage (see Peduzzi & Herold, 2005 and Pfeffer & Verrest, 2016a).

Local-level data generation began as an inclusion attempt for those traditionally excluded from numerous place-specific governance activities, such as planning and policymaking (Pfeffer, Baud, Denis, Scott, & Sydenstricker-Neto, 2013; Radil & Jiao, 2016). Traditionally, participatory inclusion of geospatial data is collected at fine spatial scales to address location-specific issues, from disaster risk reduction to ageing infrastructure (McEvoy et al., 2014; Pfeffer et al., 2013; Radil & Jiao, 2016). For this thesis, locally collected data is data collected within the boundary of an urban area by practitioners familiar with the city. Locally collected data is limited in geographical expanse but increased quality assurance as it is verified by the local knowledge of participants from the city. Consequently, proper comparison of globally available data and locally created data is needed to assess the use of geospatial data for city planning in secondary cities.

Conclusions are drawn from two case studies, focusing on each data type: local and global. Globally available data are utilized with SDG Indicator 11.3.1, where the rate of land consumption to population growth rate for 2C Initiative five cities: Denpasar, Indonesia; Esmeraldas, Ecuador; Kharkiv, Ukraine; Medellin, Colombia; and Mekelle, Ethiopia is examined. To compare limitations and benefits of each data type, I draw conclusions on the usefulness of locally collected data on urban springs in Kharkiv, Ukraine for city emergency preparedness.

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CHAPTER 2

ASSESSING SUSTAINABLE DEVELOPMENT GOAL INDICATOR 11.3.1: LAND CONSUMPTION FOR INCLUSIVE AND SUSTAINABLE URBAN GROWTH IN SECONDARY CITIES

Introduction

Secondary cities are unique environments that have generally been poorly mapped with limited data and information on infrastructure, land tenure, and planning. A secondary city is not only defined by population, size, function, and economic status, but by the neighboring and/or distant cities and their socio-economic status within the country they reside. The population of a secondary city may range between 10-50% of the country's largest city. They are urban centers providing critical support functions for governance, transportation and production services. A secondary city may emerge from a cluster of smaller cities in a metropolitan region or may be the capital city of a province, state, or second-tier administrative unit within a country. Regardless of population, common characteristics include rapid unplanned and informal growth patterns (Roberts, 2014). This dynamic growth and lack of visibility on the global stage means secondary cities are often data-poor, under-resourced, and lag behind in infrastructure and essential services (UN-HABITAT, 2016b). This creates a host of environmental security and sustainability issues that impacts the ability of governments to implement development efforts, respond to emergencies, and design sustainable futures.

The Secondary City (2C) Initiative is a field-based initiative of the Office of the Geographer, U.S. Department of State. Beginning in 2015, the 2C Initiative maps secondary cities to address resilience, human security, and emergency preparedness. The project builds local to global and public-private partnerships to create geospatial capacity, enhance data generation, local mapping, and enable science-based decision making about urban environments. These goals align with *Sustainable Development Goal (SDG) 11*, to make cities and human settlement inclusive, safe, resilient, and sustainable and *SDG Target 11.3*, to enhance inclusive and sustainable urbanization and capacity for participatory, integrated and sustainable human settlement planning and management in all countries by 2030 (UN-HABITAT, 2016a). Due to this close alignment with urban goals and our focus on geospatial data and participatory mapping, we chose to test *SDG Indicator 11.3.1* (referred to as 11.3.1), the ratio of land consumption rate (LCR) to population growth rate (PGR) or the LCRPGR ratio, on 2C Initiative cities. Specifically, 11.3.1 highlights the urgency for *participatory* human settlement planning and management by demonstrating the relations between two characteristics that measure city size – population and urban form – while integrating a *spatial* component. However, due to limited accurate demographic and spatial data for secondary cities, we speculate whether 11.3.1 is useful for small and medium sized cities.

Given the lack of detail provided for completing 11.3.1 in the monitoring guidebook, *A Guide to Assist National and Local Governments to Monitor and Report on SDG Goal 11+ Indicators,* this paper reads as a technical manual providing guidance for any secondary city to follow for next steps and applications when understanding city growth and expansion. We apply 11.3.1 to five 2C cities to examine: 1) the guidance provided for completing and interrupting 11.3.1, 2) the data recommended for 11.3.1 and additional sources of data, and 3) how to represent 11.3.1 spatially by defining ‘city’ with a spatial boundary. With this methods paper, we consider next steps and applications for understanding city growth and expansion for secondary cities and conclude with recommendations for guiding national and local governments to monitor and report on SDG goal 11-plus indicators.

Remote sensing and built-up areas

Remote sensors have revolutionized the way we observe, interpret, and classify the surface of the earth. The Global Human Settlement Layer (GHSL) of the European Commission Joint Research Centre is a spatial, thematic, temporal, high-resolution dataset built upon 40 years of Landsat imagery for mapping the global built-up areas (BUAs) divided into four epochs or time periods: 1975, 1990, 2000, and 2014 (Pesaresi et al., 2016a). In GHSL, human settlements are designated by population and physical infrastructure (Pesaresi et al., 2016a). The building is "essential to settlement infrastructure and is the basic sign of the human presence observable by remote sensing technologies" (Pesaresi et al., 2016a). With the advancement of spatial technologies, the definition of built-up has evolved to include the nature, form, structure, and spatial extent of human settlements (M. Pesaresi et al., 2015). GHSL assumes an inclusive concept of buildings, including temporary structures and informal settlements (M. Pesaresi et al., 2015). Combining GHSL with high-resolution imagery makes it possible to identify hotspots of change. The 2C Initiative uses GHSL to gain insights of change detection analysis by creating a density layer, which shows where the majority of the population growth has occurred in a particular area (Sharma, Pandey, & Nathawat, 2012).

The examination of BUAs reveal the rates and patterns of urban morphology, from which three characteristics of BUAs emerge: density, expansion, also referred to as sprawl (Angel, 2012; Inostroza, Baur, & Csaplovics, 2013; Seto, Fragkias, Güneralp, & Reilly, 2011), and land consumption (Fenta et al., 2017; Sharma et al., 2012). Indicator 11.3.1 aims to track and measure urban growth (vertical and horizontal) by calculating the LCRPGR ratio. The UN guidelines acknowledge the complexity of this concept:

> In estimating the land consumption rate, one needs to define what constitutes "consumption" of land since this may cover aspects of "consumed" or "preserved" or available for "development" for cases such as land occupied by wetlands. Secondly, there is no unequivocal measure of whether land that is being developed is truly "newly-developed" (or vacant) land, or if it is at least partially "redeveloped". As a result, the percentage of current total urban land that was newly developed (consumed) will be used as a measure of the land consumption rate. The fully developed area is also sometimes referred to as built up area. (UN-HABITAT, 2016a)

Urban growth and land consumption concerns have increased in LMICs for two reasons: 1) population increases and the rate of unplanned urban growth in LMICs (Angel, 2012) and 2) the rate at which land use and land cover has increased. Land consumption analysis is possible due to increased access to spatial data and satellite images to track these changes. While these data are increasingly less expensive and have higher accuracy (Fenta et al., 2017), access and processing satellite imagery requires internet connectivity and greater computational power.

To better understand the relationship between population growth and land consumption and to measure the change in this relationship over time and space, the Inter-Agency Expert Group on SDG Indicators (IAEG-SDG) developed a methodology to achieve Target 11.3 through 11.3.1 by calculating the LCRPGR ratio. The IAEF-SDG is composed of UN Member States and is responsible for developing and implementing the global indicator framework for the Goals and targets (UN-HABITAT, 2016a). IAEG-SDG defines PGR as the increase of a population in a country during a period, usually one year, expressed as a percentage of the population at the start of that period. IAEG-SDG developed a calculation for LCR that is still being refined. Land consumption includes: "(a) The expansion of built up area that can be directly measured; (b) the *absolute extent* of land that is subject to exploitation by an agriculture, forestry or other economic activities; and (c) the over-intensive exploitation of land that is used for agriculture and forestry" (p.30).

2C Initiative Cities

Secondary cities need geospatial methods for data collection, mapping, and analysis to better understand urban areas and growth for planning. The 2C Initiative addresses the need for data collection and geospatial analysis of cities in LMICs. Partnering with local governments, non-governmental agencies, and universities, the 2C Initiative targets data generation to map urban form, but also to train the next generation of geospatial land use experts.

From 2015 - 2019, the 2C Initiative implemented 16 projects located on four continents; six projects in Latin America (Cusco, Peru; Esmeraldas, Ecuador; Medellín, Colombia; Santa Fe, Argentina; Santiago de los Caballeros, Dominican Republic; and Tijuana, Mexico), five projects in Eastern Europe and Asia (Denpasar, Indonesia; Darkhan, Mongolia; Kharkiv, Ukraine; Indore, India; and Pokhara, Nepal), and five projects in Africa (Boke-Kamsar, Guinea; Douala, Cameroon; Mekelle, Ethiopia; Pemba, Mozambique; and Port Harcourt, Nigeria). We selected our study cities from this group.

Study Cities

We conducted an assessment of ten 2C cities and selected five cities based upon: 1) population, 2) world region, 3) city geography, and 4) 2C data themes (Table 2.1). 2C initiative cities choose 2C data themes during the city's initiation to focus project management and data collection. Although the UN-DESA dataset does not list population statistics for Esmeraldas, we selected Esmeraldas for 11.3.1 analysis to highlight data accessibility and availability challenges for small secondary cities.

Table 2.1. Five 2C Initiative test cities and their criteria to apply SDG Indicator 11.3.1.

Secondary Cities Selected for Analysis					
City	*Population*	*Year*	*World Region*	*2C Data Themes*	*City Geography*
Denpasar, Bali, Indonesia	883,814[a]	2015	Asia	Oceanic Waste Management	Island, Coastal
Esmeraldas, Ecuador	154,035[b]	2010	Latin America	Urban Environmental Security & Risk	Coastal
Kharkiv, Ukraine	1,442,204[a]	2015	Europe	Mobility, Safety, and Accessibility	Inland
Medellín, Colombia	3,735,098[a]	2015	Latin America	Urban Flows & City Growth	High valley (1500m elevation)
Mekelle, Ethiopia	440,042[a]	2015	Africa	Urban Water Resources & Planning	Highlands

[a] UN-DESA, 2018
[b] CAF Banco de Desarrollo de America Latina, 2016

Our study cities span the globe but are concentrated in the lower latitudes (Figure 2.1). They reflect the diversity found in secondary cities where the population ranges from 154,035 to over 3,000,000 and are situated in different geographic regions. However, they are similar in that all are regional seats of governance, hubs of economic activity, and centers of transportation. These study cities are all experiencing rapid, unplanned development.

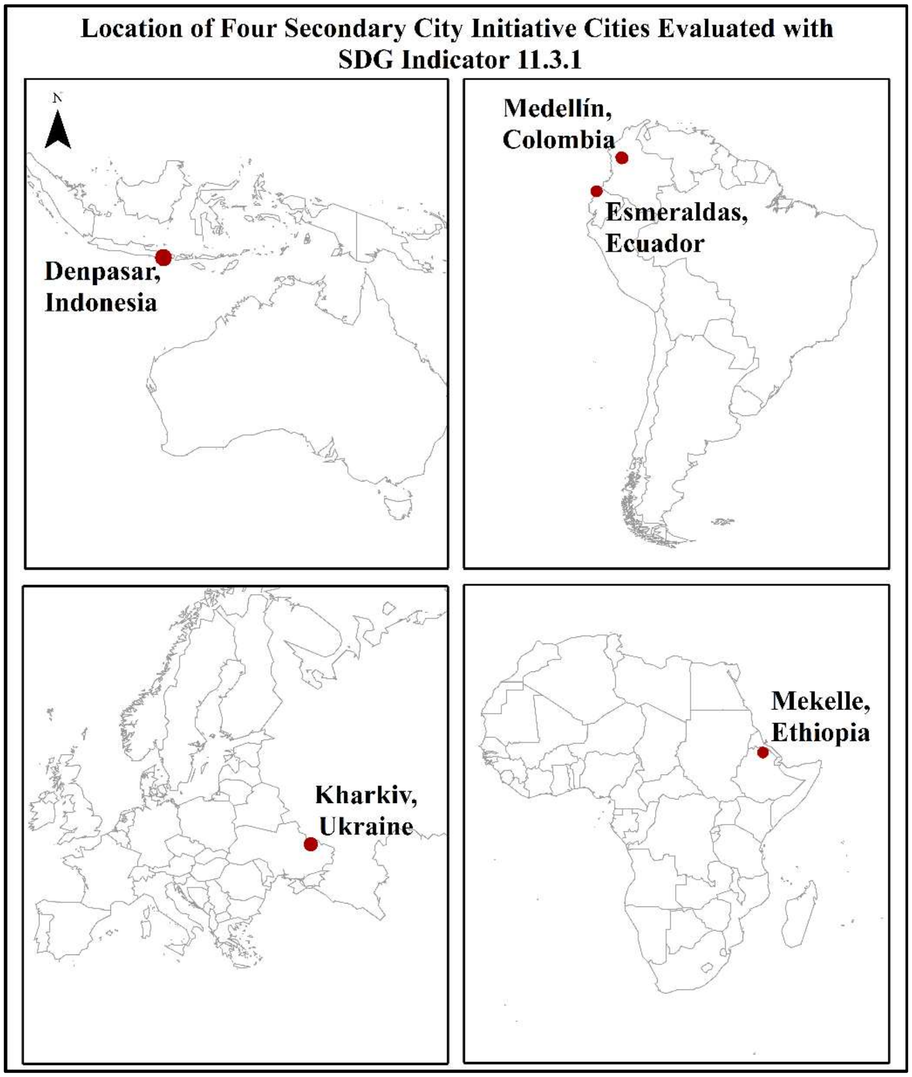

Figure 2.1: Location of four 2C initiative cities evaluated with SDG Indicator 11.3.1 calculations: Denpasar, Indonesia; Esmeraldas, Ecuador; Kharkiv, Ukraine; Medellín, Colombia; and Mekelle, Ethiopia.

Denpasar, Indonesia

Situated on the Island of Bali, Indonesia, Denpasar is the capital city of the Bali province. Bali is a popular tourist destination in Southeast Asia but is considered “the center of government, commerce, business, and education” (Prajnawrdhi, Karuppannan, & Sivam, 2015). The influx of population has affected the original character and identity of Denpasar, increasing the demand for infrastructure and services (Prajnawrdhi et al., 2015). According to the 2C partner Gringgo (a local non-governmental organization), the urban growth rate has been 2% annually from 2011 to 2016. Tourist development, inter-island migration, and rapid urban growth have contributed to waste management challenges.

Esmeraldas, Ecuador

Esmeraldas is a small, coastal city located on the north-western corner of the Ecuadorian Coast, by the mouth of the Esmeraldas River (Luque, Edwards, & Lalande, 2013). The city is a major seaport of north-western Ecuador with an oil refinery and the terminus of the Trans-Ecuadorian Pipeline. Informal settlements in Esmeraldas are characterized by a lack of property and irregular provision of basic services, such as water and electricity (Luque et al., 2013). These settlements are located in those areas of the city characterized by the greatest vulnerability, from the riverbanks of the Esmeraldas River (where there is a greater risk associated to flooding), to the uplands at the outskirts of the built area to the west of the city (where there is a greater risk associated to landslides) (Luque et al., 2013).

Kharkiv, Ukraine

Kharkiv is the administrative capital of Kharkiv Oblast and has a population of 1.44 million people in 2018 (UN-DESA, 2018b), the second largest city in Ukraine (Table 3.1). Although the majority of the population is Ukrainian both in nationality and ethnicity, the city's largest minority is of Russian descent due to its history and proximity to Russia—located approximately 40 kilometers from the Russian border. Kharkiv continues to be influenced by its proximity to Russia and the ongoing border conflict, that arguably remains the most contentious post-Soviet Union border conflict (Trenin, 2002, pg. 163).

Ukraine and Kharkiv have experienced many changes since the breakup of the Soviet Union. While Kharkiv has undergone some expansion since the early 1900's, its overall population has decreased. Much of the city's changes are related to intensification of land use and density rather than the extent of its urban footprint.

Medellín, Colombia

The Municipality of Medellín is the second-largest city in Colombia and the capital of the state of Antioquia. An estimated 60% of the city was built outside of planning controls, in the form of squatter settlements and informal development (Brand, 1995). Many citizens living in areas of informal housing lack access to running water, electricity, or waste collection services. Recently, Medellín has been recognized by the Urban Land Institute's award for the most innovative city in the world, the Verónica Rudge Urbanism Award, and the Lee Kuan Yew World City Prize, which recognizes and celebrates innovation in urban solutions and sustainable urban development and is one of 400 City Prosperity Initiative cities (www.cpi.unhabitat.org/medellin).

Mekelle, Ethiopia

Mekelle City, the capital of Tigray Regional State in northern Ethiopia, is a political, economic, and cultural center of Ethiopia (Fenta et al., 2017). Today it is the second largest city and one of the fastest growing cities in the country (Fenta et al., 2017). Rural and urban dwellers recognize the importance of water management and adequate water infrastructure due to water supply and quality challenges. In 2009, it was estimated that only 51-60% of families had access to tap water; most sought water from untreated wells, bought it from local vendors, or extracted it from shallow boreholes (Asgedom, 2014).

Methods

We developed a methodology that outline direction for small- to medium-sized cities to complete 11.3.1. The UN suggests two data sources for 11.3.1 calculations: GHSL (M. Pesaresi et al., 2015) to calculate LCR, and the World Urbanization Prospects (WUP) dataset, "Cities Over 300,000" (2018 revision, file 12) compiled by the UN Department of Economic and Social Affairs (DESA), Population Division to calculate PGR (UN-HABITAT, 2016a). We followed the suggested guidelines and joined the WUP (tabular) and GHSL (spatial) datasets to calculate the LCRPGR ratio.

GHSL shows change in the human presence on the planet since 1975 (Pesaresi et al., 2016a). GHSL data are available in 38-meter, 250-meter, and 1-kilometer resolution for the predefined epochs: 1975, 1990, 2000, and 2014 (Pesaresi et al., 2016b). Although GHSL data are appropriate to calculate LCR, the data require preliminary remote sensing analysis before they are ready for calculation (UN-HABITAT, 2016a). Data from GHSL for the years 1975 (initial) and 2014 (final) define a 39 year measurement period (UN-HABITAT, 2016a). The WUP dataset consists of population statistics from country censuses (UN-DESA, 2018a). Data for the years 1975 (initial) and 2015 (final) define a 40 year measurement period (UN-HABITAT, 2016a).

The urban agglomeration is the recommended study area for all SDG 11 Indicators (UN-DESA, 2018b). According to UN-DESA, an urban agglomeration is comprised of the city center and surrounding suburbs, forming a continuous urban settlement (UN-HABITAT, 2016a). When data on the urban agglomeration are not available, the UN notes the change in scale and definition in the 'statistical concept' or 'agglomeration definition' column of the WUP dataset (UN-DESA, 2018a). Urban agglomeration population data were used for Denpasar, Kharkiv, Medellín, and Mekelle (Table 2.2); their statistical concepts are the city proper, city proper, metropolitan area, and city proper, respectively (we acquired population data for Esmeraldas through different means, which we address below). The census sources and definitions of urban populations for each country can be found in the UN-DESA "Sources for Urban Population" dataset (UN-DESA, 2018b).

Table 2.2: United Nations World Urbanization Prospects (WUP) 1975 and 2015 population amounts for Denpasar, Indonesia, Kharkiv, Ukraine, and Mekelle, Ethiopia.

UN World Urbanization Prospects Urban Agglomeration Population Amounts for Denpasar, Kharkiv, and Mekelle		
City	*1975 Population*	*2015 Population*
Denpasar	104,513	883,814
Kharkiv	1,352,608	1,442,204
Mekelle	41,883	440,042

Spatial boundaries

We calculated the BUA for 11.3.1 by clipping the GHSL to three spatial boundaries for each of the five cities to compare spatial differences in land consumption (Table 2.3). We chose to clip GHSL to three different boundaries based off three compounding considerations: 1) the need to define consumption (UN-HABITAT, 2016a, pg.30), 2) the continuous nature of the GHSL that requires delimiting a study area to calculate LCR (Martino Pesaresi, Melchiorri, et al., 2016), and 3) lack of official spatial definition, or geospatial boundary, for 'city.' In order to designate the amount of BUA to include as land consumption, we chose to define consumption with the boundaries below (Figure 2.2). In addition, we do not know the spatial boundary WUP population amounts are measured and recorded; we know the WUP urban agglomeration statistical concepts for Denpasar, Kharkiv, and Mekelle are are the city proper, metropolitan area, and city proper.

Table 2.3: Total area of the DIVA-GIS Boundary, Local City Boundary, and 2C Bounding Box for Denpasar, Indonesia; Esmeraldas, Ecuador; Kharkiv, Ukraine; Medellín, Colombia; and Mekelle, Ethiopia in square kilometers.

Total Area of Three Spatial Boundaries			
City	*Local City Boundary (km^2)*	*DIVA-GIS Boundary (km^2)*	*2C Bounding Box (km^2)*
Denpasar	125.76	132.48	927.4
Esmeraldas	72.39	44.55	348.37
Kharkiv	291.25	350.62	1,334.11
Medellín	383.24	361.13	988.13
Mekelle	196.32	24.3	267.34

We decided to complete 11.3.1 using three *open-source* boundaries: the DIVA-GIS boundary, local city boundary, and Secondary Cities Bounding Box (2C bounding box) (Figure 2.2). 2C partners provided the local city boundary, which is a predefined boundary officially recognized by the nation or region. The five cities local city boundaries and subsequent metadata are accessible on the 2C GeoNode, an open-source data repository for data visualization and download (see http://secondarycities.geonode.state.gov/). The following metadata about each city boundary is from the 2C GeoNode. Denpasar's local city boundary was created by Badan Informasi Geospatial Information Agency of Indonesia (www.bakosurtanal.go.id/). Esmeraldas' local city boundary was created by GAD Municipal de Esmeraldas. Kharkiv's local city boundary data was exported from a geodatabase provided by SPAERO, a geospatial consulting company in Ukraine. Mekelle's local city boundary was provided from Mekelle University, updated in 2015. Medellín's local city boundary was provided by the Medellín Administrative Department of Planning (https://www.medellin.gov.co/irj/portal/medellin).

The DIVA-GIS boundary is from http://www.diva-gis.org/, a free computer program for mapping and analyzing geographic data. In addition, DIVA-GIS acts as a data repository, providing free spatial data including administrative areas (Hijmans, Guarino, & Mathur, 2012). DIVA-GIS is primarily for those who cannot afford generic commercial GIS software (Hijmans et al., 2012). DIVA-GIS sources the administrative areas from www.GADM.org version 1, whose initiative is to map administrative areas of all countries using high resolution imagery.

Lastly, we derived the 2C bounding box as part of the 2C Initiative by creating a minimum bounding box from two to five-kilometer buffers around the DIVA-GIS boundary to ensure surrounding urban areas would be included for analysis. This boundary captures emerging urban areas and peri-urban regions. This boundary dictates how the 2C initiative has 'defined consumption' for this SDG analysis. All 2C Initiative data processing use this boundary for derivative data layers.

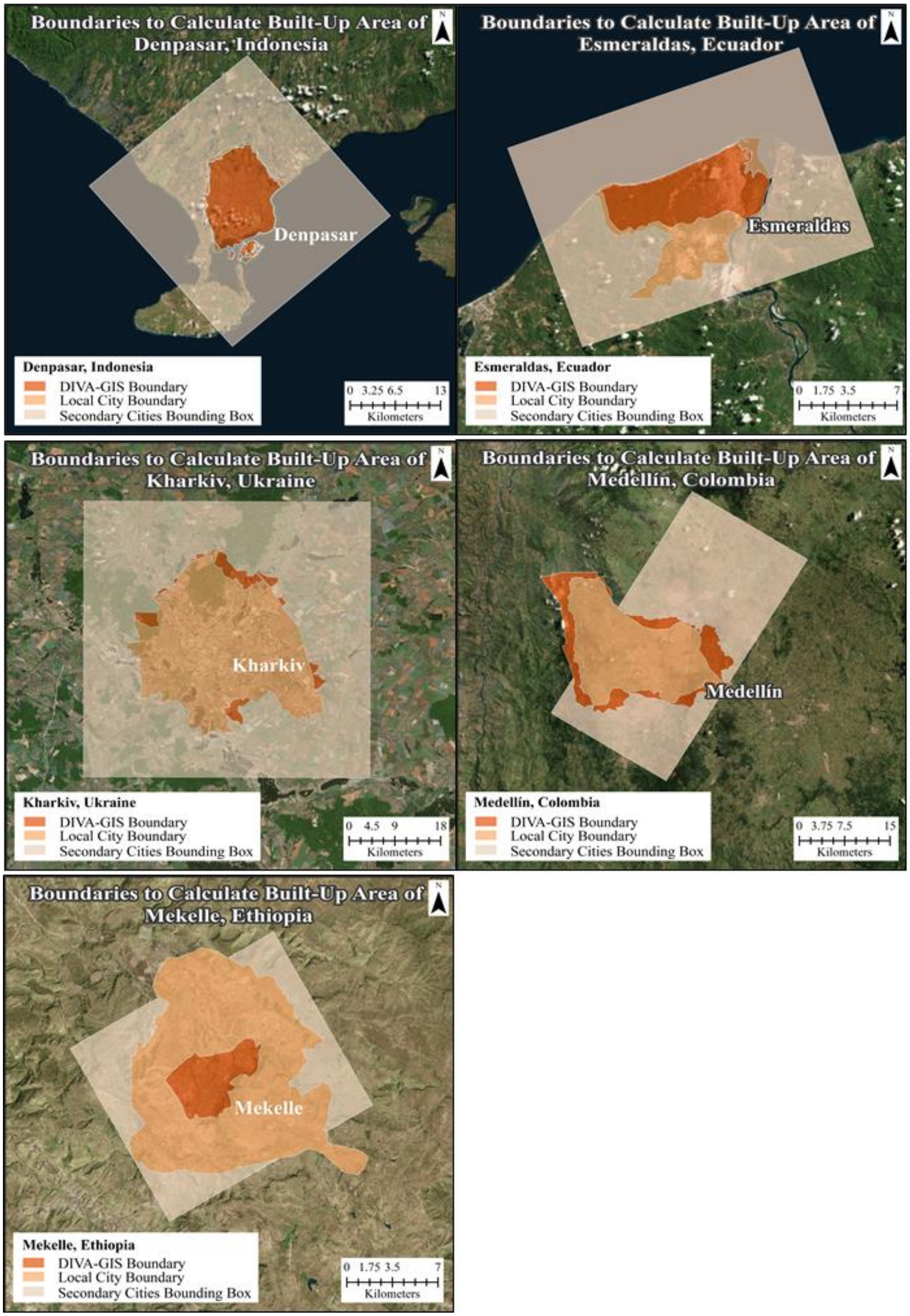

Figure 2.2: Local City Boundary, DIVA-GIS Boundary, and Secondary Cities Initiative Bounding Box. Base imagery sourced from ESRI ArcGIS basemap products (source: AeroGRID, CNES/Airbus DS, DigitalGlobe, Earthstar Geographics, GeoEye, IGN, USDA, USGS, and the GIS User Community).

Methods Flowchart

The methods flowchart illustrates our methodological process to calculate PGR (Figure 2.3), BUA, LCR, and LCRPGR (Figure 2.4). Every step of the 11.3.1 calculation is outlined as clear direction for small- to medium-sized cities to be able to complete 11.3.1. Given the lack of detail provided in the monitoring guidebook, the flowchart and calculations that follow are a direct example any city can follow.

We downloaded the WUP (https://population.un.org/wup) and GHSL datasets (https://ghsl.jrc.ec.europa.eu) [1]. The WUP dataset contains population data for 1,859 cities from 1950 to 2035 (UN-DESA, 2018b). We obtained data for Denpasar, Medellín, and Mekelle from 1975 and 2015 [2a]. GHSL contains three folders: population, built, and settlement. We calculated 11.3.1 with data from the built folder.

Calculating population growth rate

For PGR, if the candidate city had a population of 300,000 inhabitants or more, we used the WUP dataset for that city. We sought a source other than the WUP dataset for cities with populations less than 300,000 [2b]. Once we determined the population, we calculated the measurement period (final year – initial year) and calculated PGR [3]. PGR comprises the number of births and deaths during a given period and the number of people migrating to and from a country (UN HABITAT, 2016). The equation for PGR is (UN HABITAT, 2016):

$$PGR = \frac{\ln(Pop_{t+n}/Pop_t)}{y} \tag{2.1}$$

where Pop_{t+n} is the total population within the city in the current/final year, Pop_t is the total population within the city in the past/initial year, and y is the number of years between the two measurement years (measurement period) (UN HABITAT, 2016).

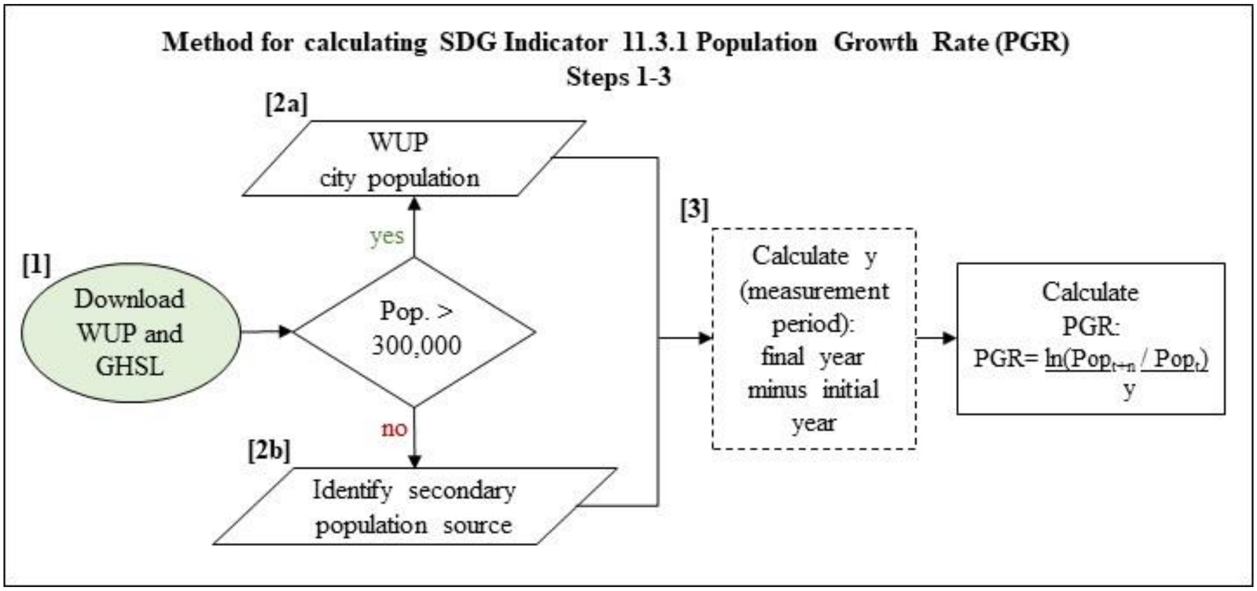

Figure 2.3: Steps to complete population growth rate (PGR) calculation from SDG Indicator 11.3.1. Step [1] is downloading World Urbanization Prospects (WUP) dataset from UN Department of Economic and Social Affairs. Step [2a] acquires the data from the WUP. Step [2b] is only necessary if the city has a population less than 300,000; obtain population data from a secondary source as the WUP only provides population data for cities with population greater than 300,000. Step [3] calculates the measurement period and PGR.

Calculating land consumption rate

We further processed our data to calculate the land consumption rate (Figure 2.4). We uploaded GHSL to Google Earth Engine (GEE) and clipped the dataset to the DIVA-GIS boundary, local city boundary, and 2C bounding box for all five cities. GEE is a spatial platform for scientific analysis and visualization of geospatial datasets that hosts and stores satellite imagery, including GHSL, in a public data archive (Gorelick et al., 2017) [4].

After creating three raster files from GHSL, we reviewed each city's data mask. The data mask is a separate raster dataset that relays whether the GHSL algorithm can generate epochs (Pesaresi et al., 2016a, p. 12). The GHSL data mask mosaic has values of 1 through 16, which indicate how many and which epochs have available data [5]. Value 10 indicated that data were available for 1975 and 2014 epochs for two cities (Denpasar and Mekelle). Because data were not available for the same epochs for the other two cities (Esmeraldas and Medellín), we did not continue 11.3.1 calculations. We decided to analyze cities with data available for those epochs because it was the longest period of time to show the greatest change.

We loaded the GHSL raster files into ESRI ArcGIS Desktop 10.5.1 (ArcMap) and calculated the BUA in square kilometers (km^2) [6]. The GHSL BUA is the union of all areas where buildings can be found as prescribed by GHSL (Pesaresi et al., 2016b). Once we computed the BUA, we calculated the measurement period and completed the LCR equation [7].

LCR parameters include: 1) the expansion of BUA that can be directly measured; 2) the absolute extent of land that is subject to agriculture, forestry, and other economic activities; 3) the over-intensive exploitation of land for agriculture and forestry (UN-HABITAT, 2016a). The LCR equation is (UN-HABITAT, 2016a):

$$LCR= \frac{nl(Urb_{t+n}/Urb_t)}{y} \tag{2.2}$$

where Urb_{t+n} is the total areal extent of the urban agglomeration in km^2 for the current year, Urb_t is the total areal extent of the urban agglomeration in km^2 for the past/initial year, and y is the number of years between the two measurement years (measurement period) (UN-HABITAT, 2016a).

Calculating the Land Consumption/Population Growth Ratio

We divided LCR by PGR, which resulted in the LCRPGR ratio (Figure 2.4) [8]. The LCRPGR ratio represents urban expansion in relation to urban area (UN-HABITAT, 2016a). Working with secondary cities and the assumption they are growing in population and land expansion, if the LCRPGR ratio is greater than one, the urban agglomeration's land consumption rate is greater than the population growth rate. If the LCRPGR ratio is less than one, the population growth rate is greater than land consumption. LCRPGR ratios close to one mean the

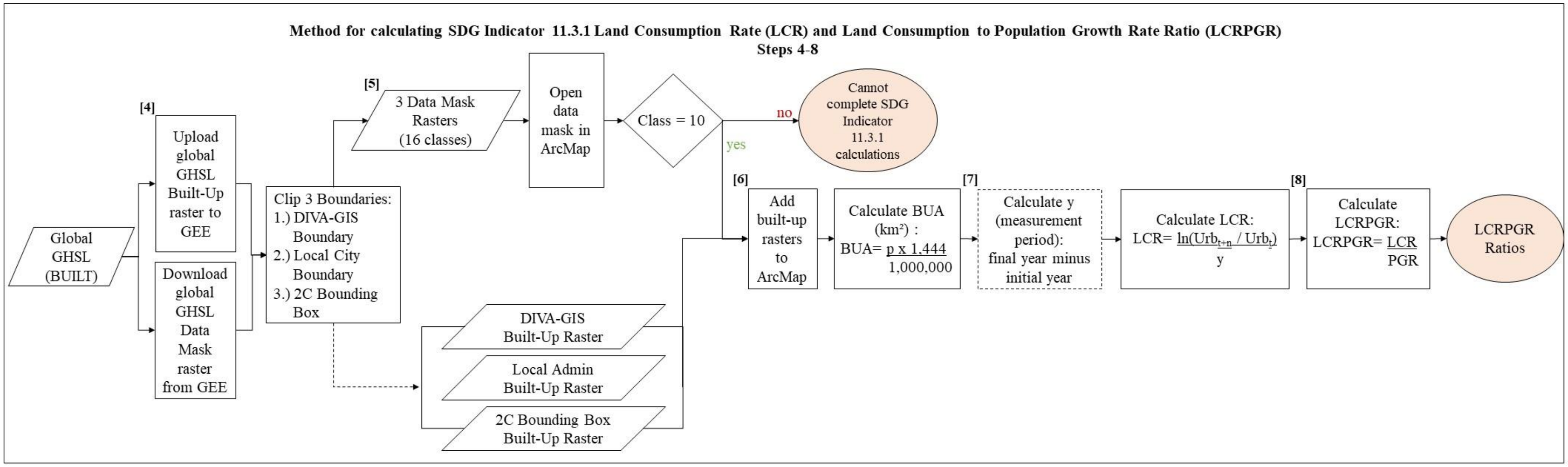

Figure 2.4: Steps to complete land consumption rate (LCR) calculation and land consumption rate to population growth rate (LCRPGR) ratio from SDG Indicator 11.3.1. Step [4] is uploading the built-up and data mask rasters to Google Earth Engine (GEE). Step [5] loads the data mask raster into ArcMap to clarify if data is available for epochs needed (class 10). If the data mask indicates data is available, step [6] adds the built-up rasters to ArcMap and calculates the built-up area (BUA). Step [7] calculates the measurement period and LCR. Step [8] calculates the LCRPGR.

area of interest had competitive LCR and PGR. [8]. To calculate LCRPRG, we divided LCR by PGR in the following equation (UN-HABITAT, 2016a):

$$LCRPGR = \frac{LCR}{PGR} \tag{2.3}$$

Operationalizing SDG Indicator 11.3.1 calculations

The population data for Denpasar, Medellín, and Mekelle were available from WUP 1975 and 2015 since these cities are larger than 300,000. Esmeraldas has a population less than 300,000. The recent census data for Esmeraldas (2010) recorded an estimated population of 154,035 (CAF Banco de Desarrollo de America Latina, 2016). For the initial year of data, we collected population data from the Ecuadorian 1974 census (INEC, 2010), the same source UN-DESA used for larger Ecuadorian cities in the WUP (UN-DESA, 2018b). Although we acquired population data for Esmeraldas and Medellín, we were not able to calculate the LCR because the GHSL data mask did not have BUA data for the measurement period we identified.

We calculated 11.3.1 using the same population data for all three boundaries for Denpasar and Mekelle. Using Denpasar as an example, the recorded WUP population was 104,513 in 1975 and 883,814 in 2015. Denpasar's population grew seven-fold between 1975 and 2015.

After determining Denpasar's population, we uploaded GHSL data into GEE and clipped it to Denpasar's local city boundary, which shows human settlement for Denpasar. We calculated the BUA. Denpasar's local city boundary had 2,491 pixels classified as built-up for 1975 and 54,768 pixels for 2014. We converted the number of pixels into area (m^2) by multiplying the sum of pixels by the area of a pixel in meters (m) (38 m x 38 m = 1,444 m^2), then into km^2 by dividing by 1,000,000:

$$BUA = (p \times 1{,}444)/1{,}000{,}000 \tag{2.4}$$

where p is the number of pixels in the GHSL raster files. When we compared the initial and final epochs of data for Denpasar, the BUA grew from 3.6 km^2 to 79.1 km^2 over a period of 39 years, from 1975 to 2014.

The PGR equation (Equation 2.1) takes the natural log of the initial population, 104,513, divided by the final population, 883,814. We divided the natural log of the quotient by 40 years, the measurement period for the population, 1975 to 2014. Denpasar's PGR result for the local city boundary was -0.053. We then calculated the LCR equation (Equation 2.2), multiplied the natural log of the initial BUA, 3.60 km^2, divided by the final BUA, 79.15 km^2. We divided the natural log of the quotient by 39 years, the measurement period for the BUA, 1975 to 2014. The local city boundary for Denpasar had an LCR of -0.079. Finally, we divided -0.079 (LCR) by -0.053 (PGR), which resulted in an LCRPGR ratio of 1.49 (see Appendices A and B for Denpasar and Mekelle's complete 11.3.1 calculations). Denpasar's LCRPGR ratio, which was greater than one, indicates a greater increase in land consumption than the population growth for the city.

Results

LCRPGR results for Secondary Cities Initiative cities

Using the GHSL and WUP datasets and three spatial boundaries for two cities, we calculated and compared nine LCRPGR ratios for three secondary cities (Table 2.4). Denpasar, Kharkiv, and Mekelle had LCRPGR ratios greater than one, revealing greater LCR than PGR. The LCRPGR ratio results for all three boundaries were consistent in that LCR was greater than PGR.

Denpasar had small differences between ratios, with LCRPGR ratios of 1.49 for the local city boundary, 1.50 for the DIVA-GIS boundary, and 1.46 for the 2C bounding box. Kharkiv's LCRPGR ratio resulted in 6.89 for the local city boundary, 6.33 for the DIVA-GIS boundary, and 9.81 for the 2C bounding box. The high LCRPGR ratios indicate a significantly greater land consumption rate to population growth rate for Kharkiv. Mekelle had LCRPGR ratios of 1.69 for the local city boundary, 2.34 for the DIVA-GIS boundary, and 1.67 for the 2C bounding box. LCRPGR ratios farther from 1 attest to greater divergence between rates. For example, an LCRPGR ratio of 2.34 had a greater rate of land consumption than an LCRPGR ratio of 1.46. LCRPGR ratios close to 1 mean the area of interest had competitive LCR and PGR.

DIVA-GIS boundaries have the smallest total area and therefore LCRPGR ratios closest to one. The 2C bounding boxes have the greatest total area and therefore, LCRPGR ratios farthest from one. Although population data stayed consistent for each city's boundary, the extent of the area increased, causing the LCRPGR ratio to decrease.

Table 2.4: SDG Indicator 11.3.1 land consumption rate to population growth rate ratio results for two of the Secondary City (2C) Initiative cities: Denpasar, Indonesia, Kharkiv, Ukraine, and Mekelle, Ethiopia. Results are shown for three spatial boundaries: local city boundaries, DIVA-GIS boundaries, and 2C bounding box.

SDG Indicator 11.3.1 Land Consumption/Population Growth Rate Ratio Results			
	City		
Boundary	Denpasar	Kharkiv	Mekelle
Local City Boundary	1.49	6.89	1.70
DIVA-GIS Boundary	1.50	6.33	2.32
2C Bounding Box	1.46	9.81	1.67

Built-up area

Despite Denpasar's 2C bounding box having more than double the amount of BUA in 2014 compared to the DIVA-GIS boundary and local city boundary (Table 2.5), Denpasar had a negligible difference between LCRPGR ratios (Figure 2.5). Because the LCR and PGR equations (Equations 2.3 & 2.4) are logarithmic, double BUA does not equate to a doubled LCRPGR ratio. In addition to the log scale effect, one of the consequences of using the same population data for three boundaries with different degrees of BUA is that ratios are less likely to show discrepancies in LCRPGR values.

Table 2.5: Built-up Area from Global Human Settlement Layer (GHSL) for three spatial boundaries used to complete Sustainable Development Goal (SDG) Indicator 11.3.1.

Global Human Settlement Layer (GHSL) Built-Up Area for Denpasar, Kharkiv, and Mekelle in square kilometers		
	1975 BUA (km^2)	*2014 BUA (km^2)*
Denpasar		
DIVA-GIS Boundary	3.68	83.44
Local City Boundary	3.60	79.15
2C Bounding Box	8.37	174.30
Kharkiv		
Local City Boundary	194.50	299.19
DIVA-GIS Boundary	176.12	261.67
2C Bounding Box	241.79	446.49
Mekelle		
DIVA-GIS Boundary	0.02	4.77
Local City Boundary	0.19	9.39
2C Bounding Box	0.21	9.45

In general, Denpasar's BUA in 1975 was barely visible at a 15 km scale. In contrast, the DIVA-GIS boundary and local city boundary in 2014 are not large enough to encompass the city center (Figure 2.5). If our results were dependent on the DIVA-GIS boundaries and local city boundary, we would have lost an important part of the city center that extends southward. Due to visual observations of satellite imagery regarding the city's growth and the need to create wider boundary for the 2C Initiative, we were able to capture land consumption in both the north and south of the city with the 2C bounding box. As population increases within the boundary, the LCRPGR ratio should also increase.

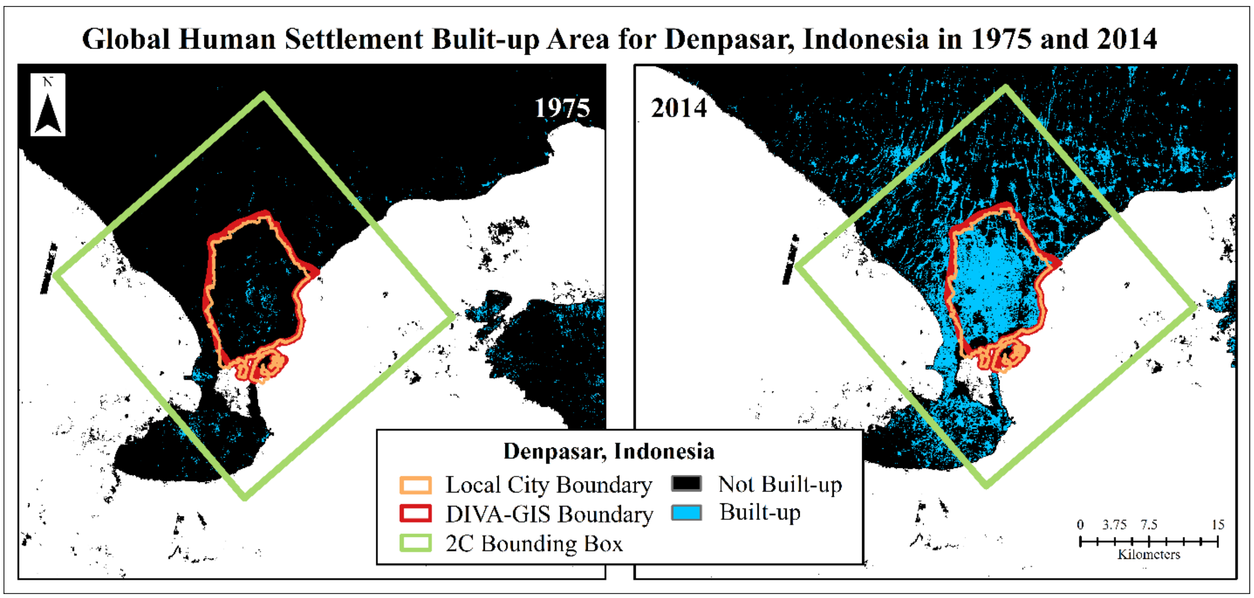

Figure 2.5: Map of Global Human Settlement built-up areas for Denpasar, Indonesia for two epochs (1975 and 2014), including three spatial boundaries: local city boundary, DIVA-GIS boundary, and Secondary Cities (2C) Initiative bounding box.

For Kharkiv, LCRPGR ratios are significantly greater than one because the population change between 1975 and 2015 did not grow exponentially compared to Denpasar and Mekelle. Kharkiv's population increased from 1,352,608 to 1,442,204 over 40 years (UN-DESA, 2018b); that is 107% growth compared to Denpasar and Mekelle's seven-fold growth. As the PGR was lesser over 40 years, *any* change in LCR dramatically increased the LCRPGR.

Similar to Denpasar, we see the local city boundary and DIVA-GIS boundary have a lesser difference between them. This difference can be justified by looking at the BUA within the separate boundaries (Figure 2.6). The local city boundary and DIVA-GIS boundary have similar amounts of total area and BUA.

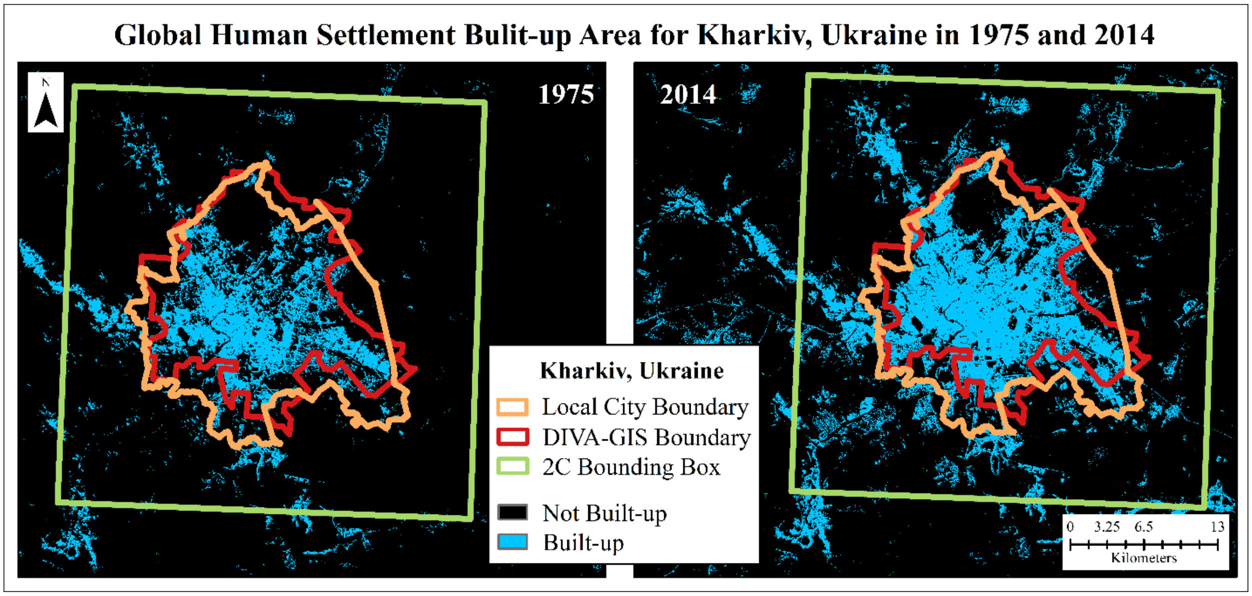

Figure 2.6: Map of Global Human Settlement built-up areas for Kharkiv, Ukraine for two epochs (1975 and 2014), including three spatial boundaries: local city boundary, DIVA-GIS boundary, and Secondary Cities (2C) Initiative bounding box.

Mekelle's boundaries had a greater difference between LCRPGR ratios. The DIVA-GIS boundary for Mekelle was double the amount of LCR compared to PGR (Table 4). In general, Mekelle's BUA in 1975 was not visible (Figure 2.7). The DIVA-GIS boundary in 2014 does not extend to fully contain the city center. Although the 2C bounding box and local city boundaries include a larger area of peri-urban, not-BUAs, they also encompass the whole city center. Unlike Denpasar, all three boundaries are different sizes and extents, indicating the importance of including a range of boundaries in the analysis. This produced lower LCRPGR ratios closer to 1 for the 2C bounding box and local city boundary resulting in similar conclusions as Denpasar.

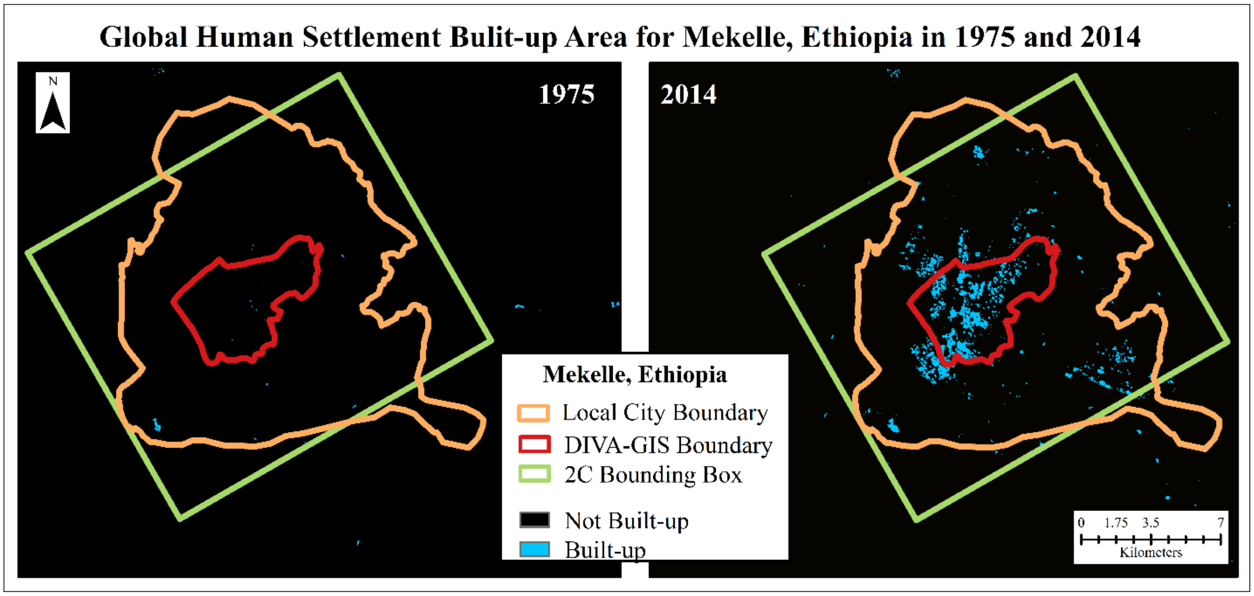

Figure 2.7: Map of Global Human Settlement built-up areas for Mekelle, Ethiopia for two epochs (1975 and 2014), including three spatial boundaries: local city boundary, DIVA-GIS boundary, and Secondary Cities (2C) Initiative bounding box.

Discussion

We encountered a number of limitations to globally available data that made calculating 11.3.1 questionable for secondary cities in LMICs, including data acquisition, accuracy, and interoperability. Secondary cities have limited resources with respect to geospatial technology and Internet accessibility and connectivity. Computer technology updates (both hardware and software) are difficult to maintain, but are needed for higher processing speeds, better results, and time efficiency.

Calculating 11.3.1 with the same population data for all three boundaries skews results. More BUA increased the LCRPGR ratio. We presume increasing population amounts to reflect larger geospatial boundaries, in this case the 2C bounding box, equates to an LCRPGR closer to one. We were not able to formally draw conclusions on this due to a limited number of cities we examined. Ratio results are interrupted assuming these cities are growing in population and land consumption. If one compared rural cities decreasing in population and maintaining similar land consumption (Cohen, 2006), the LCRPGR is below zero because the PGR is negative while the LCR is positive. Regardless, to complete 11.3.1, population data for the PGR should emulate the changing areas under analysis.

Indicator 11.3.1 guidelines do not include instructions on how to calculate the BUA for a city. We were able to calculate BUA because we applied GHSL BUA calculations to three different spatial boundaries for each city. We chose three boundaries in order to test and compare results between boundaries, even though these boundaries are not officially recognized jurisdictions.

Statistics for countries with urban agglomerations under 300,000 are difficult to find. Due to the nature of our partnership through the 2C Initiative, we were able to acquire credible population data for Esmeraldas. Obtaining population data for cities with a population under 300,000 requires either knowledge of another language to translate population data from local sources, or local contacts to provide reliable data. A common characteristic among secondary cities is rapid growth. Due to limited resources, transient and immigrant populations, and impoverished populations living in informal settlements, many secondary cities are not able to plan or account for changing growth patterns even when the population is greater than 300,000, making these statistics difficult to attain (Marais, Nel, & Donaldson, 2016).

Another issue associated with completing 11.3.1 relates to Internet connectivity and accessibility. As we completed research, GHSL became available for downloading and process on GEE. Although the data are more readily available through GEE, data expertise and adequate computer technology are required for secondary cities to process GHSL. This can be costly for cities that are already limited in resource and expertise.

Associated to GHSL becoming available of GEE, the pace at which technology changes affected completing 11.3.1. In addition to the availability of GHSL in GEE, a new WUP dataset and a new version of Esri's ArcGIS became available. We incorporated these updates to improve our results but spent additional time re-processing and analyzing data and recreating maps.

GHSL is a one-of-a-kind spatial dataset due to its long temporal scale and fine resolution (Martino Pesaresi, Melchiorri, et al., 2016). As a result, obtaining spatial population datasets and other sources for urban extent calculations was not possible. The 2C Initiative collects data through participatory mapping, which include human geography data on hazards, risks, locations of vulnerable populations, including the recommended data for land consumption (GHSL) and population data. Although 11.3.1 recommended WUP data for population, the 2C Initiative collects population data from WorldPop (see 2C GeoNode for WorldPop data on 2C Initiative cities, www.secondarycities.geonode.state.gov/). WorldPop (GeoData Institute, University of Southampton) is an open-source spatial dataset that identifies the number of people per pixel at 100-meter to 1-kilometer resolution. Although it might have contributed to 11.3.1, its resolution is not conducive for a city scale and does not have the same temporal coverage GHSL has. GHSL has a population dataset, which is as 250-meter resolution, even coarser than WorldPop and not ideal for urban environments (Freire et al., 2015; Pesaresi et al., 2016a).

Over the course of this research we had to modify our approach due to limited GHSL data availability and differences in LCRPGR ratios between cities' boundaries. Since the question of data accuracy arose subsequent to our initial Esmeraldas and Medellín results, we realized our city selection criteria should have included data accuracy assessments. We refocused the methodology and results to the three spatial boundaries that provided more insight into each city's growth than simply producing the LCRPGR ratio.

Conclusions

This paper reveals step-by-step methodology to complete 11.3.1 for all cities, especially small- to medium-scaled cities in LMICs. Overall, the results show Denpasar, Kharkiv, and Mekelle are consuming land faster than population growth is occurring, regardless the boundary used for completing 11.3.1. Furthermore, results reveal the LCRPGR ratio is greatly affected by how land consumption is defined because the boundaries needed to define an area of interest determined the BUA calculated for the LCR, altering the LCRPGR results. If the LCRPGR ratio is used to inform if the city is growing in versus growing out, then informed spatial boundary selection including local input is best to choose a boundary representative of the urban area in question. Because of this, we recommend identifying and applying boundaries that are consistent with city jurisdictions, and identifiable land consumption areas. We would not have been able to spatialize 11.3.1 without identifying spatial boundaries that are inclusive of dynamic city zones. Otherwise, our results would ignore important city areas.

We completed fewer results on 11.3.1 due to limited data availability, difficulty in data operability, and the overall objective of looking at data for small- to medium- scale cities. However, continuing to work under the assumption that secondary cities are the fastest growing cities in developing countries (Roberts, 2014) and that these cities are growing in population and land expansion (UN-HABITAT, 2016b), we presume the results would be the same for any city in the same category. Additional analyzes may be completed on different categories of cities, such as megacities or cities whose population has decreased, should a researcher be interested in such results.

Our results show the importance of identifying how and where small- to medium-sized cities in the LMICs are expanding, especially as “a 1% annual decline in average densities in developing countries is projected to quadruple the urban land area by the year 2050" (UN-HABITAT, 2016b, p. 129). Because secondary cities are constantly evolving in size, area, density, and composition, city boundaries and jurisdictions are in flux. For example, one city that is currently part of the 2C Initiative is in the middle of undergoing a citywide jurisdiction transition.

Not only does the 2C Initiative provide local data that does not otherwise exist, the initiative creates and fosters geospatial user networks with universities, private sector workers, municipal employees, and non-governmental organizations. Our partners are familiar with their city providing local knowledge to identify where and what land is being consumed and the local dynamics of population growth. We recommend consulting with local experts to validate the type of development in BUAs, which would assist in validating GHSL data for 11.3.1 and other global datasets for SDG indicators that rely on geospatial data.

Ultimately, globally available data can provide guidance in identifying and examining trends, however, localizing the indicator by using local input is an important next step for these kinds of analyses. Our results indicate these three cities are consuming land; they are not as representative of data collected at a local scale to characterize the form and fabric of the city – nor do they tell us why the city is changing. Data verification and participatory mapping through 2C Initiative partners and participants help spatialize the results and provide insights into the drivers causing urban changes. This research and the 2C Initiative lay the groundwork for next steps. Next steps involve further exploration of SDG 11.3 by evaluating Indicator 11.3.2 to assess the proportion of cities with a structure of civil society participation in urban planning and management that operates regularly and democratically.

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CHAPTER 3

CAPACITY OF URBAN SPRINGS TO SUPPORT POPULATIONS IN CASE OF EMERGENCY, A SECONDARY CITY CASE STUDY: KHARKIV, UKRAINE

Introduction

Water resources and their management are essential for achieving sustainable development as water is required to ensure human securities are met (UN-Water, 2013). Access to safe and sufficient drinking water in order to meet basic needs is an initial step to water security (UN-Water, 2013). As secondary cities are under-resourced and lag behind in infrastructure and essential services, they experience their own variety of potable water problems (Richey et al., 2015). Examples include limited access to drinking water, rapid water depletion due to increased population, water collection timing, and vulnerability to contamination by disasters such as flooding (UN-HABITAT, 2003; UN-Water, 2013). If alternative approaches could be implemented effectively, alternative waters resources would be sufficient to combat drinking water scarcity in LMICs (UN-HABITAT, 2003).

Inaugurated in 2015, the Secondary City (2C) Initiative utilizes field-based participatory mapping for data generation to help developing cities prepare for resilience, human security, and emergency preparedness. Housed in the Office of the Geographer in the U.S. Department of State, the project builds public-private partnerships to create geospatial capacity by creating new data, enhancing data generation, and enabling science-based decision making about urban environments. 2C Initiative cities choose their own goals to focus on throughout the project. From 2015 - 2019, the 2C Initiative implemented 16 projects located on four continents; six projects in Latin America, five projects in Eastern Europe and Asia, and five projects in

Africa. Three of sixteen 2C Initiative cities struggle with flooding (Douala, Esmeraldas, and Port Harcourt); one city is focused on ocean waste management (Denpasar); an additional three cities focus on water procurement for cities (Kharkiv, Mekelle, and Santiago). Half the 2C Initiative cities have expressed the need to focus on water. Globally, secondary cities have water issues.

Initiated by the American Association of Geographers, Kharkiv joined the 2C Initiative in its first year partnered with agencies around the city. The 2C Kharkiv project focuses on development of geospatial data for urban safety and emergency preparedness. 2C Kharkiv collects data for vulnerable populations, including the elderly, people with disabilities, gender-based vulnerabilities, and internally-displaced persons through workshops at Karazin University in Kharkiv. Three general categories describe the data: mobility, community resources/services, and public safety. As of 2015, 2C Kharkiv partners had collected 2,417 point features on mobility features, 1,496 point features on social infrastructure, and 18,039 features on public safety (Fesenko, Fesenko, & Bibik, 2017) using Survey 123 for ArcGIS (referred to as Survey 123). 2C Kharkiv has been successful at building local capacity by strengthening collaboration between Kharkiv universities and municipality and generating data on vulnerable populations that provide the basis to enhance city response to community needs.

This paper focuses on local data collected during a 2C Initiative workshop conducted in May of 2016 to assess the utility of locally collected, verified data for informed decision-making. Through a participatory data collection method, 2C Kharkiv partners collected geospatial data and information on urban springs, or natural springs within city limit, and how citizens use these 26 urban springs within Kharkiv, Ukraine. From the results, 2C Kharkiv partners inform district authorities which springs can support the population closest to them.

Secondary cities and water

According to Sivakumar (2010), the estimated global population increase is a main factor contributing toward a “bleaker future for water planning and management in developing countries.” Estimates by UN Water states that currently more than 2 billion people live in countries experiencing high water stress, which affects every continent, hinders sustainability, and limits social and economic development (UN Water, 2018). Water stress occurs when demand for water exceeds the available amount during a certain period (EEA, 2018).

The lack of water as a basic resource to vulnerable populations has been studied since the 1980’s. In 1998, Gadgil (1998) outline water security issues in LMICs, from the associated health issues to the economics and politics that influence water in LMICs. Over ten years later, Sivakumar (2010) elaborates on the continuing need for water and sanitation in LMICs, outlining the growing disparity between providing water and how the lack water is threatening communities. Sivakumar (2010) discusses the illogical disparity; people are increasingly contaminating freshwater resources, yet vast numbers of people lack clean drinking water. Enormous quantities of water become available during heavy rainfall periods but is not collected and utilized for potable water. Instead, heavy rainfall period are increasingly threatening communities in at-risk locations and damage environments. In 2018, the *UN Sustainable Development Goal 6 Synthesis Report on Water and Sanitation* report estimated 31 countries in LMICs experiencing water stress between 25% and 70%, or the beginning of water stress to seriously stressed. Another 22 countries are above 70% and under serious water stress (UN Water, 2018).

In secondary cities the procurement of potable water is an issue. Kikpatrick (2004) stated, “In developing counties, an essential requirement for economic growth and sustainable development is the provision of efficient, reliable, and affordable infrastructure services, such as water and sanitation...” Although there was an increase in the 1990s of private foreign investment in infrastructure projects to aid infrastructure development (Kirkpatrick, 2004), water infrastructure still is not efficient for drinking water security as infrastructure systems are archaic and out-of-date (Vystavna et al, 2018). Establishing reliable distribution system to disseminate potable water is critical for citizen health improvements (Lee & Schwab, 2005).

Groundwater has emerged as a main alternative for renewable water resources in developing countries (Gadgil, 1998; Vrba & Renaud, 2016). Currently, surface water is the main freshwater supply of potable water globally, but the importance of groundwater is increasing as surface water becomes less reliable and predictable (Richey et al., 2015). For example, in many arid and semi-arid regions, groundwater resources have become the main source of available potable water (Mays, 2013; Vrba & Renaud, 2016). Groundwater sources exhibit low vulnerability to hazards events and can serve as a safe source of freshwater in the aftermath of disasters (Gadgil, 1998; Vrba & Renaud, 2016). It is therefore important to identify, investigate, and protect these groundwater resources to ensure depletion and contamination does not happen (Gadgil, 1998; Lee & Schwab, 2005; Mays, 2013; UN-HABITAT, 2003).

One area of water resources needing more advancements is supplying water after emergencies. Groundwater plays an important role in disaster-related emergencies (Vrba & Renaud, 2016). A situation becomes a disaster when they impact vulnerable people and infrastructure (Vrba & Renaud, 2016). One of the major goals in providing water during an emergency is to provide potable water to the affected population (Loo, Fane, Krantz, & Lim, 2012). Getting the potable water to populations consists of two main challenges: water quality problems and limited access to infrastructure and resources (Loo et al., 2012). Previously, bottled water and water tankers were delivered to the areas in need, however, naturally occurring water resource are more practical and sustainable than continuously delivering water (Loo et al., 2012).

Many factors can be taken into consideration when recommending quantity of water for daily potable water consumption, such as body weight, environmental temperature, physical activity, respiratory loses, and transport loses. In the World Health Organization (WHO) *Guidelines for Drinking-Water Quality*, guideline values make recommendations based on a 60 kg adult consuming 2 liters per day from drinking water, which would be equivalent to 3 liters per capita per day including food consumption (pg. 83; Howard and Batram, 2003). In LMICs, White et al. (1972) and Gleick (1996) suggest that a minimum of 3 liters per capita per day is required for adults in most situations.

Springs require little maintenance and are free of contaminants that would cause public health issues making them an ideal resource in LMICs, but literature on springs for citizen consumption is difficult to find, at best. Springs have been identified as an area of research that is under examined and are globally threatened ecosystems (Davis, Kerezsy, & Nicol, 2017; Richey et al., 2015); Springer and Stevens (2008) noted that there was no consistent or comprehensive classification system for springs. Springs tap groundwater sources that have been filtered through layers of soil and rock and are isolated from the surface and discharge at the Earth's surface (Burch & Thomas, 1998; Davis et al., 2017). Therefore, spring water is generally free from pathogen contamination and therefore ideal for potable drinking water (Burch & Thomas, 1998). Due to their isolated nature and comparatively small spatial extent, it seems realistic that conservation actions are more feasible and cost effective for springs than other water sources (Davis et al., 2017). As spring systems rely on groundwater, the protection of the groundwater resource the springs derive from must be a fundamental protection priority (Davis et al., 2017). This requires country, regional, and municipal authorities' knowledge to protect groundwater.

Geospatial data for urban water

Geospatial technologies are key to water management for cities in LMICs. Geospatial technologies produce, manage, monitor, circulate, and contest spatial knowledge (Pfeffer & Verrest, 2016). They play an integral role for growing urban areas, providing resources from data generation, analysis, and visualization (Harris, 1989). By using geospatial data and technologies for development purposes, such as access to springs in cities, geospatial data is an ideal platform for urban planners, policy-makers, and general public to understand, participate in, and influence holistic urban processes (Foth, Bajracharya, Brown, & Hearn, 2009; Tao, 2013). Geospatial data, specifically the data from participatory mapping, address issues specific to a city, initiating the ability to implement sustainable urbanization practices at the local level (Collier et al., 2013). Participatory mapping is a research method where spatial information is a core component (Brown, Strickland-Munro, Kobryn, & Moore, 2017).

Participatory mapping opens opportunities for citizen interaction in city urban planning, decision-making, and community action processes by facilitating citizen involvement in participatory mapping (Collier et al., 2013). While participatory mapping still consists of primitive data and information (ie: point, lines, polygons, adding photos to existing data), growth in the field continues to emerge (Collier et al., 2013), which can be seen in the 2C Initiative. In Kharkiv, Ukraine, 2C Kharkiv partners facilitated a workshop in May of 2016 with students at Karazin University in which the students collected and mapped urban springs points in and around Kharkiv with discharge amounts in liters per second (L/s).

As locally, integrated, purposeful geospatial datasets are essential building blocks of viable infrastructure information (Collier et al., 2013), 2C Initiative cities collect and disseminate data through workshops. Partners upload the data to the 2C Initiative GeoNode, an open-source data repository for data visualization and download (see http://secondarycities.geonode.state.gov/). Subsequently, all locally collected and derived data is available to anyone from anywhere with an internet connection. Research in this paper focuses on urban springs data collected by locals during a 2C Initiative workshop in Kharkiv, Ukraine May of 2016.

Kharkiv, Ukraine and its urban springs

Kharkiv is the administrative capital of Kharkiv Oblast and has a population of 1.45 million people (UN-DESA, 2018b), the second largest city in Ukraine. Although the majority of the population is Ukrainian both in nationality and ethnicity, the city's largest minority is of Russian descent due to its history and proximity to Russia—located approximately 40 kilometers from the Russian border. Kharkiv was founded in 1654 as a small fortress. It grew to become a major center of Ukrainian culture within the Russian Empire. It functioned as the first capital of the Ukrainian Soviet Socialist Republic until January 1935, when the capital relocated to Kiev. Kharkiv continues to be influenced by its proximity to Russia and the ongoing border conflict.

While Kharkiv has undergone some expansion during this time, its overall population has decreased. Much of the city's changes are related more to intensification of land use and density rather than the spatial extent of its urban footprint. The need for sustainable water resource management has become consequentially important to Kharkiv's growth.

Kharkiv City's tap water is supplied from two sources: the Seversky Donets River and Dnipro-Donbass channel that supplies the Krasnopavlivka Reservoir. The Seversky Donets River supplies the majority of water intake with 430,000 square meters (m^2) retrieved daily. The secondary intake from the Krasnopavlivka Reservoir is 130km south of the city and supplies 140,000m^3 of water per day. Urban water supply and sewage infrastructure were built during the Soviet period (1960s–1980s) and were not completely renewed until now. About 97% of the total population of Kharkiv uses centralized drinking water supply system with a total length of 1,867 km (Vystavna et al, 2018). Tap water treatment system is not the safest for drinking due to out-of-date chlorination for treatment and aged pipelines that are decades old. To date, the water infrastructure of the Kharkiv city has been deteriorating due to the lack of financing, labor, and equipment, causing numerous leakages, which cannot be usually eliminated in a short time (Vystavna et al, 2018). Despite the fact that official data states tap water meets all quality requirements, citizens do not use tap water for drinking and cooking because of unsuitable taste and smell. Tap water quality is partly solved by in-house filtration systems, however, as the filters are quite expensive, some citizens are not willing to invest in filters (WHO, 2011).

Another source for drinking is groundwater taken from artesian wells 630 to 700m of deep. Water from the artesian wells is distributed throughout the city by delivery trucks and water bottles. This water is drinkable and naturally treated through soil and rock filtration, similar to natural springs. However, these water resources are limited because of very low natural replenishment rates in the aquifer posing risks for water exhaustion. Nevertheless, due to high extraction costs, citizens are reluctant to purchase artesian well water (Mays, 2013).

In addition to the artesian wells, there are 26 urban springs within the city boundaries equipped for decentralized water consumption. The urban springs flow from the Obukhiv aquifer in fissured fine-grained sandstone rocks of Eocene age lying 30 to 40m below the surface (Vystavna et al, 2018). The upper layers are composed of permeable sand, loams and clay providing natural treatment of water during infiltration. The aquifer is cut by the Lopan, Kharkiv, and Udy rivers river valleys (Vystavna et al, 2018). Quaternary sands and loams are several shallower springs flowing out from the upper layers.

Currently, urban springs are not the primary source of drinking water in Kharkiv, but in many cases are preferred by Kharkiv citizens. Urban springs in Kharkiv serve as recreational sites as well as a resource in times of emergency. Water from urban springs is popular amongst Kharkiv citizens because is it cleaner than tap water. Although the urban springs water contains elevated concentrations of nitrate, chloride, and sulfates from time-to-time, the concentration amounts are not dangerous (Davis et al., 2017).

Citizens collect from the spring nearest to their place of residence. As the Kharkiv municipality started to notice an increase of citizens visiting urban springs to collect water, authorities built aesthetic and leisurely resources, making the springs a recreational past time for elderly and women with children, mostly. These improvement resources include playgrounds, toilets, stairs, canopies covering the outlets, benches, and empty bottles for purchase. Despite the higher quality of safe water and daily recreational pleasures that makes Kharkiv residents happier, the urban springs in Kharkiv is trusted more by the citizens and it’s a main source of water currently not utilized by the municipality (Figure 3.1).

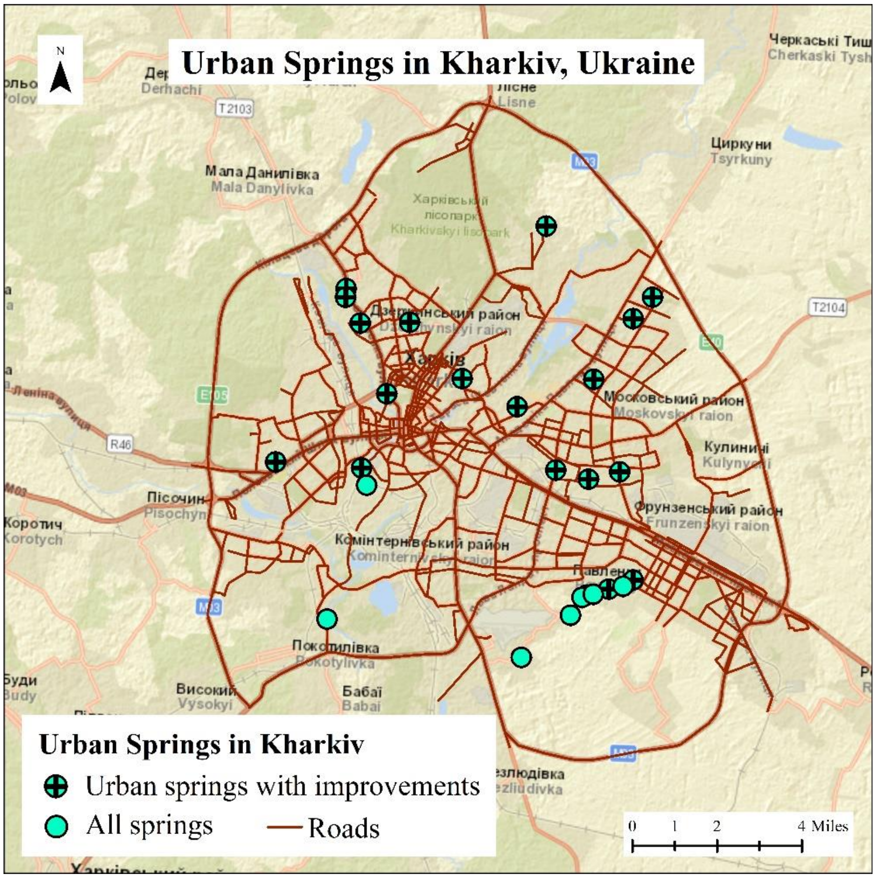


Figure 3.1: Map of urban springs with improvements in Kharkiv, Ukraine. improvement resources include playgrounds, toilets, stairs, canopies covering the outlets, benches, and empty bottles for purchase.

Besides the recreational and daily enjoyment achieved by the springs, emergency situations in the past have proven the need to understand the capability of the spring in case of future emergency. For example, in 1995, heavy rains produced an extreme flooding situation that put Kharkiv in a state of emergency as the sewer system and water system flooded (Clarke, 1995). The urban springs were used during the state of emergency to provide citizens drinking water.

Data and Methods

Two data sources are used to assess the number of citizens each spring can support given the amount of discharge versus the total population closest each spring: a point file on urban springs in Kharkiv (Figure 3.2) and WorldPop, a continuous, global population raster dataset that displays the number of people per pixel. WorldPop population data provided all population data and totaled population amounts used for the analysis (www.worldpop.org/). WorldPop is a globally available raster dataset initiated in 2013 with the aim of producing detailed and freely-available population distribution and composition maps for Latin America, Africa, and Asia (WorldPop, 2019).

2C Kharkiv partners at Karazin University in Kharkiv collected local data on urban springs by conducting the workshop in May of 2016 where students at the university mapped urban springs points in and around Kharkiv with discharge amounts in liters per second (L/s) using Survey 123 (Figure 3.2). Survey 123 is a simple and intuitive form-centric data gathering solution for creating, sharing, and analyzing surveys (arcgis.com). With Survery123, collectors ask a survey question, answer the question, and map their answer.

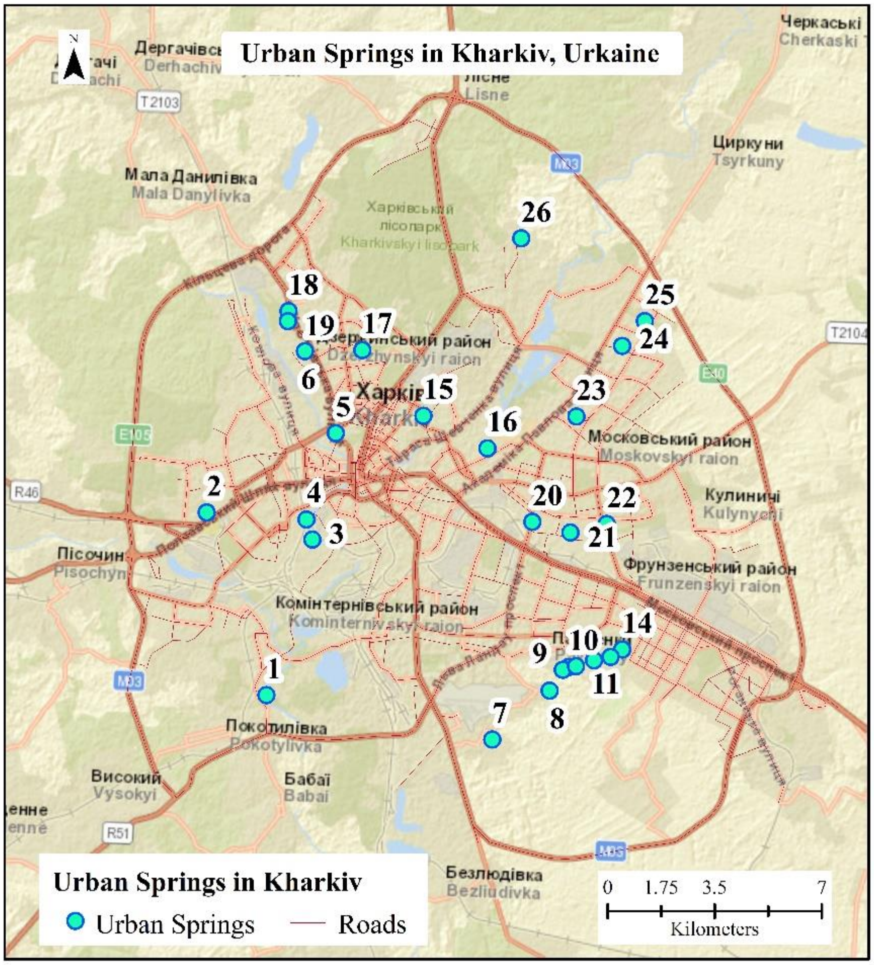


Figure 3.2: Map of urban springs in Kharkiv Ukraine. Base imagery sourced from ESRI ArcGIS basemap products (source: AeroGRID, CNES/Airbus DS, DigitalGlobe, Earthstar Geographics, GeoEye, IGN, USDA, USGS, and the GIS User Community).

Employing Survey123, the amount of discharge at each spring was recorded on 26 springs using a stopwatch and 5L or 6L container. The results were converted into L/s (Figure 3.3). 2C Kharkiv patterns used the urban spring data for additional research on protecting recharge zones of the springs (see Vystavna et al., 2018). Their methodology accounted for Seasonal fluctuations and were incorporated into the data. The resulting data were used for this paper. No data on urban springs in Kharkiv previously existed.

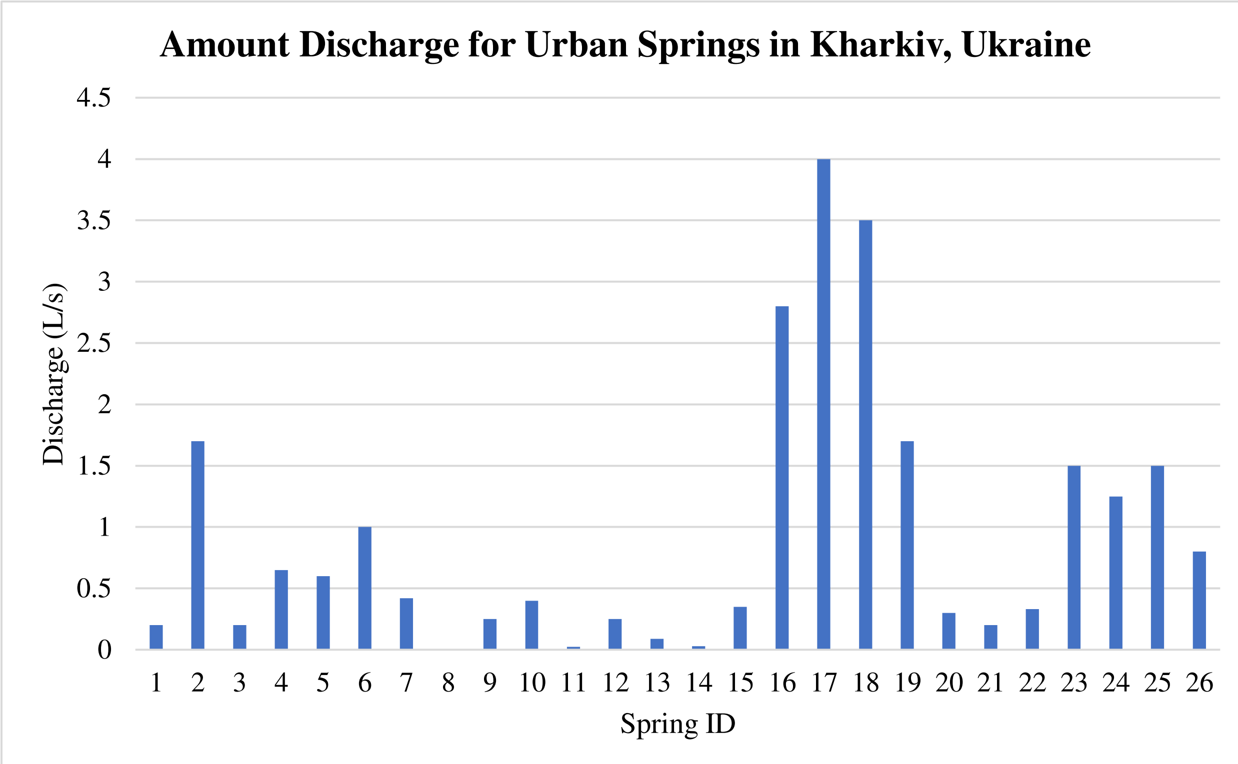


Figure 3.3: Discharge amounts for twenty-six urban springs throughout Kharkiv, Ukraine in liters per second.

Urban springs for potable water in an emergency

Under the presumption *everyone* collects water from the springs during the case of emergency, we completed the following analysis delving into the population closest to each spring and the ability of that spring to support the nearest populations. 2C Kharkiv partners providing recommendation to district authorities of urban spring water availability is important in order to direct citizens to water procurement options should the centralized water system be turned off or in another case of emergency—such as the flooding in 1995.

Analysis began by establishing a pattern of water consumption (Figure 3.4). Given the recommendation from WHO *Guidelines for Drinking-Water Quality* (2011, pg. 83), we completed the analysis on procurement of 2L over 24 hours of access. Establishing a pattern of consumption quantitively provides an estimation of the amount of water each spring must provide for surrounding citizens to utilize the spring during an emergency. The following calculation was used to calulate the amount of people each urban spring could support given the amount of discharge in L/s and each person collecting 2L of water at any point of the day:

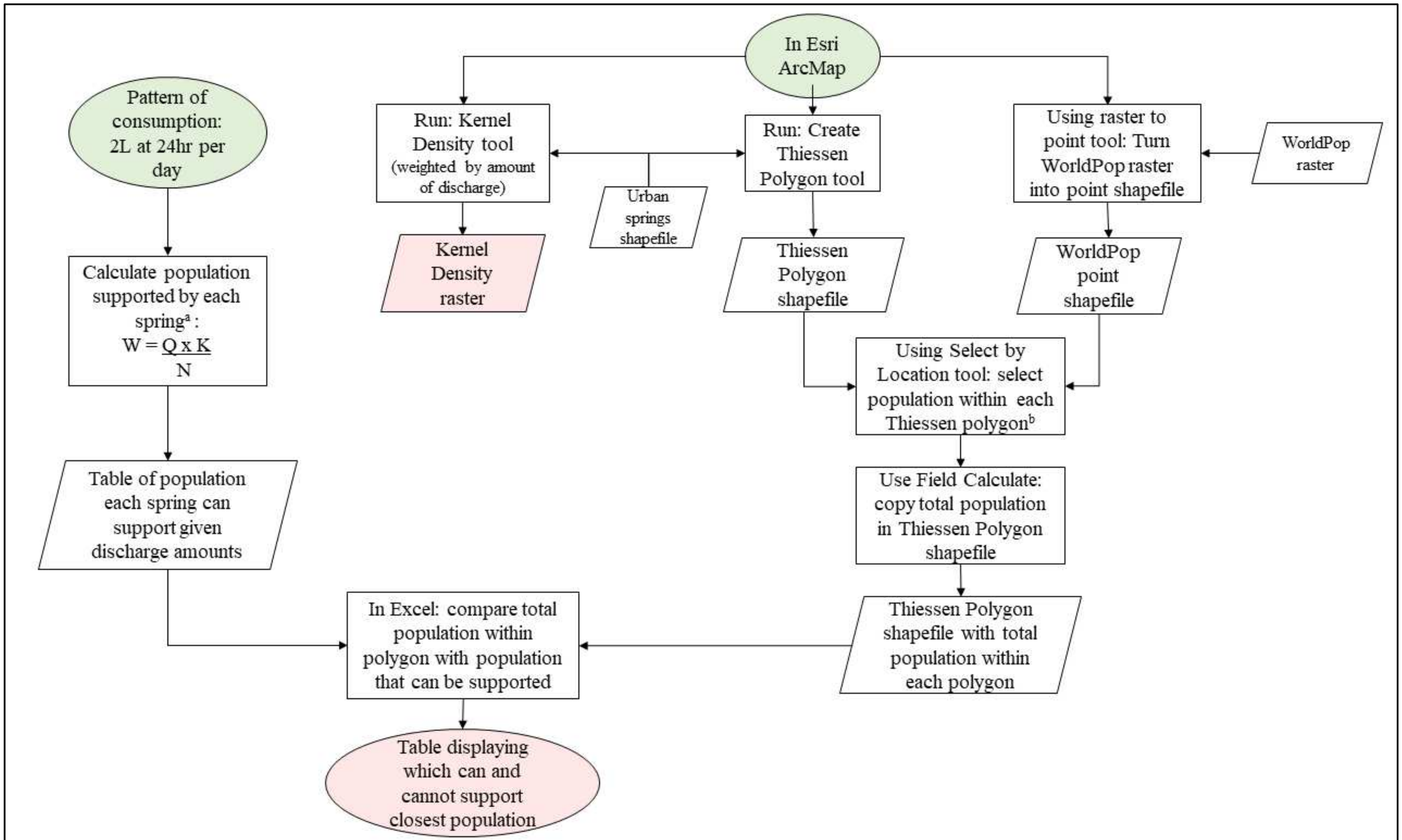
$$W = \frac{Q \times K}{N} \tag{1}$$

where: W is the number of people, Q is the discharge of a spring in L/s, K is the number of second in 24 hours, 86,400 seconds, and N is water consumption at 2L per person per day.

Next, we mapped the density of springs with the greatest amounts of discharge using the Kernel Density tool in ArcMap. We weighted the Kernel Density tool by the amount of discharge. Kernel Density calculates the density of point features around each output raster cell (Esri, 2016). Kernel density allows us to see area(s) within the city with greater amounts of spring discharge in conjunction with the densest area(s) of the city in regard to population.

Continuing to work under the assumption citizens go to the spring nearest them, the Create Thiessen Polygon tool was used on the springs to determine percentage of population from the WorldPop dataset closest to each spring. Each Thiessen polygon contains only a single point input feature, in this case an urban spring, and any feature within a Thiessen polygon is closest to its associated point than to any other point input feature (Esri, 2018). Comparing disseminated population amounts within each Thiessen polygon with the resulting consumption pattern totals displays if everyone nearest that spring can be supported by that spring in case of emergency. The Create Thiessen Polygon tool generates its own self-defining rectangle, which was then used to mask the WorldPop data.

Lastly, in order to find the total number of citizens closest to each polygon, the WorldPop raster was turned into a point file including the population per pixel in each point. Then, we used the Select by Location tool in ArcMap to field calculate the sum of population from the WorldPop dataset to each associated Thiessen polygon.



[a] W = the number of people; Q = the discharge of a spring in L/s; K = the number of second in 24 hours, 86,400 seconds; N = water consumption at 2L per person per day

[b] Population within Thiessen polygon is closest to that spring

Figure 3.4: Methods flowchart to compare to the number of citizens each urban spring can support given the amount of discharge to the total population closest each spring in Kharkiv, Ukraine. Establish a pattern of consumption: 2 hours over 24 hours of access. In Esri ArcMap, run the Kernel Density tool using the urban springs shapefile to see area(s) of Kharkiv with clusters of springs that have large discharge amounts. Run the Create Thiessen Polygon tool using the urban springs shapefile. Everything within the Thiessen polygons is closest that spring. Lastly in Esri ArcMap, turn WorldPop raster (www.worldpop.org/) into point shapefile using Raster to Point tool. Finally, in Microsoft Excel, create a table to compare the total population.

Results

We calculated the total number of people supported by each spring at 2L over the 24 hour day. Totaling the number of people supported at this pattern of consumption, 1,038,701 citizens can procure water from the urban springs in Kharkiv if the centralized water system gets shut off or another emergency occurs (Table 3.1). That is almost three-fourths the population, 74.19%. This means one-fourth the population, 25.81%, will have to procure water from a different source, such as bottled water from the grocery store.

Table 3.1: Total amount of people each spring can support given its amount of discharge in Kharkiv, Ukraine.

Quantity of people supported by each urban spring in Kharkiv, Ukraine		
Spring ID	Amount Discharge (L/s)	Quantity of consumers provided with spring water (2L 24hr)
1	0.2	8,640
2	1.7	73,440
3	0.2	8,640
4	0.65	28,080
5	0.6	25,920
6	1	43,200
7	0.42	18,144
8	0.003	130
9	0.25	10,800
10	0.4	17,280
11	0.023	994
12	0.25	10,800
13	0.088	3,802
14	0.03	1,296
15	0.35	15,120
16	2.8	120,960
17	4	172,800
18	3.5	151,200
19	1.7	73,440
20	0.3	12,960
21	0.2	8,640
22	0.33	14,256
23	1.5	64,800
24	1.25	54,000
25	1.5	64,800
26	0.8	34,560
	Total	**1,038,701**
% of total population (1.4M)		**74.19%**

2C Kharkiv providing district authorities a kernel density map allows them to see area of the city with the greatest amount of discharge available for citizens in the case of an emergency (Figure 3.5). In this case, the greater clustering of springs with the largest amount of discharge is located to the northwest of the city. Given accessibility to complete data, ideally springs kernel density is compared to a density map of population. This equates the densest populous of Kharkiv with the northwest area of the city. As accurate data of Kharkiv is currently being created, using the globally available dataset, WorldPop, and the Thiessen tool, I calculated the percentage of population within each Thiessen polygon.

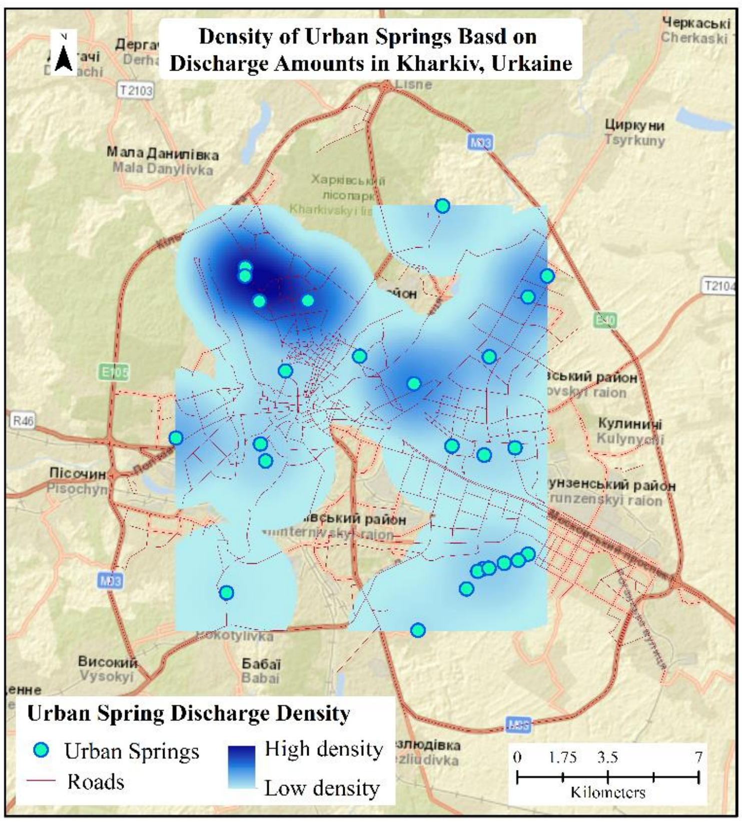


Figure 3.5: Map displaying density of discharge amounts from urban springs in Kharkiv, Ukraine. High density areas equate to areas of several springs with high amounts of discharge. Areas of low density indicate areas of the city with fewer springs and springs with lesser discharge amounts. Base imagery sourced from ESRI ArcGIS basemap products (source: AeroGRID, CNES/Airbus DS, DigitalGlobe, Earthstar Geographics, GeoEye, IGN, USDA, USGS, and the GIS User Community).

Comparing the number of citizens that can be supported by each spring with the total population within each Thiessen polygon from WorldPop, 10 of the 26 urban springs have sufficient discharge to support the population closest it (Table 3.2). Because the results displayed at least one-fourth the population of Kharkiv require alternative sources of water during an emergency regardless, we knew some springs would not be able to support the closest population. 2C Kharkiv completing additional analysis that compares the amount of excess discharge a spring produces with a raster of population density shows authorities additional options of where citizens can access spring water in case of emergency. For example, Spring 10 produces enough discharge for an additional 10,000 citizens. Spring 9 may have the option of referring citizens to spring 10 instead.

Table 3.2: Total population amounts within Thiessen polygons created from urban springs in Kharkiv, Ukraine, and the difference between the number of citizens the spring can support and how many citizens are closest that spring.

Difference between amount of Discharge and Total Discharge Needed for Population Nearest each Urban Spring in Kharkiv, Ukraine						
Spring ID	*Discharge (L/s)*	*Amount of citizen supportable: 2L at 24hr*	*Total population within Thiessen*	*Percent of total population within Thiessen*	*Difference in population supported*	*Can spring support population?*
1	0.2	8,640	55,619	3.72%	(46,979)	no
2	1.7	73,440	122,950	8.22%	(49,510)	no
3	0.2	8,640	120,801	8.08%	(112,161)	no
4	0.65	28,080	46,922	3.14%	(18,842)	no
5	0.6	25,920	77,429	5.18%	(51,509)	no
6	1	43,200	45,759	3.06%	(2,559)	no
7	0.42	18,144	72,862	4.87%	(54,718)	no
8	0.003	130	21,821	1.46%	(21,691)	no
9	0.25	10,800	22,604	1.51%	(11,804)	no
10	0.4	17,280	6,860	0.46%	10,420	yes
11	0.023	994	877	0.06%	117	yes
12	0.25	10,800	2,643	0.18%	8,157	yes
13	0.088	3,802	2,591	0.17%	1,211	yes
14	0.03	1,296	115,280	7.71%	(113,984)	no
15	0.35	15,120	74,043	4.95%	(58,923)	no
16	2.8	120,960	77,809	5.20%	43,151	yes
17	4	172,800	60,122	4.02%	112,678	yes
18	3.5	151,200	85,437	5.71%	65,763	yes
19	1.7	73,440	25,343	1.69%	48,097	yes
20	0.3	12,960	93,755	6.27%	(80,795)	no
21	0.2	8,640	34,353	2.30%	(25,713)	no
22	0.33	14,256	88,003	5.88%	(73,747)	no
23	1.5	64,800	74,971	5.01%	(10,171)	no
24	1.25	54,000	33,363	2.23%	20,637	yes
25	1.5	64,800	26,936	1.80%	37,864	yes
26	0.8	34,560	106,574	7.13%	(72,014)	no

Discussion

For the daily use of the springs, additional survey information is needed about the different demographics using the springs and the amount of water collected. 2C Kharkiv partners collecting information on the age structure of who visits these springs briefs Kharkiv City officials on how many people daily procure water from the springs, in addition to informing the city of future improvements ideas appealing to a spring's daily visitor. For example, a larger percentage of women with children visiting the springs during the day suggests more playgrounds are best improvements for the daily demographic.

In case of emergency, completing a network analysis assesses the travel ability and reality of citizens to get to other parts of the city if a spring does not support its closest citizens. Completing a network analysis or path distance analysis requires more insight from individuals about how they access the water. There are several transportation networks available throughout Kharkiv that allow for citizens to get to water sources. Kharkiv has a functioning road network, metro way, and railway, in addition to multipurpose alternative transportation paths that are walkable. Although all these transportation networks are available, they may not be the best for obtaining water given an emergency.

Lastly, to assess the ability of a handicapped or disabled citizen's access to a spring and the improvements that can be made to ensure all have access, additional information on the handicap accessibility is needed. Complete data of ramps available or flat-access springs ensures equality for Kharkiv's citizenry.

A benefit of working with local partners in Ukraine is their ability to critique results and refine the methodology as analysis is being completed. Since they have local knowledge and are familiar with the city, partners in Kharkiv reviewed data and suggested improved methods processes and analyses that created relevant results for water planning recommendations to the city. Although very helpful, it decelerated the methods process as we updated methodology with 2C Kharkiv partners newly recommend data and analyses. One example we experienced was obtaining population amounts from WorldPop. After review of the dataset by 2C Kharkiv partners, they reported WorldPop not representative of population density although the total population in WorldPop is comparable to local numbers. An accurate and locally trusted dataset is incomparably important to continue assessing the role of urban springs for emergency preparedness in Kharkiv. This is why next step recommendations include analysis with locally collected population data to accurately denote the living locations of citizens. Completing this accurately spatializes the correlation between the amount of discharge each spring has available and where the density of population is in Kharkiv.

Another benefit of working with locally collected data verified by locals is the geographic boundary is already defined. Due to the nature of globally available data being continuous, a boundary is needed to define the area of interest. For this paper, we clipped WorldPop to the urban springs' extent.

Conclusions

Utilizing the springs during a case of emergency requires additional knowledge of where the population in Kharkiv is living, as well as a plan for district authorities so they can be confident when recommending to citizens which springs to access during an emergency.

Locally collected data, urban spring data, has its limitations same as globally downloaded data, WorldPop data. The urban springs data was locally verified by Kharkiv citizens, however, data attributes collected about the springs are often limited to collector's opinions or experiences with the springs and little-to-no backup by literature justifies the attributes collected. For example, the urban springs data contains a field on handicap accessibility denoting the presence of wheelchair ramps. Additional resources defined by literature on what makes something accessible guides attribute collection of other handicap accessible resources at the springs.

There were also political and bureaucratic limitations to accessing or processing locally collected data such as private companies or governments not wanting data released for undeclared, secretive reasons. This was the case specifically with the urban springs data, however, data on water pipes is not available due to continued Russian influence and piping installation happening during the Russian unrest era.

As stated above, the WorldPop data provides a total population amount comparative to local numbers. The population data does not however represent the density of population which provides insight of areas where the majority of the population lives.

Ultimately, reliable or complete data for secondary cities continues to be unavailable for secondary city resilience, human security, and emergency preparedness. Considering the number of next steps and possible alternatives for data in the case study of Kharkiv, the lack of adequate geospatial data for city planning is affecting emergency management options aiding citizen safety during the case of an emergency.

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CHAPTER 4

CONCLUSION

Conclusions comparing data types

My initial hypothesis comparing globally available data with locally collected data presumed locally collected data is the better option for analyzes that inform city planning and development assessments and decisions. From the conclusions drawn with the case studies laid out in this thesis, I conclude locally collected data is the first option, however, the two datasets *can* complement each other given benefits to globally available data and limitations to locally collected data that are important to consider.

Globally available data is at the fingertips of everyone, even people in developing countries, given the current global internet enterprise (Pfeffer & Verrest, 2016). With appropriate resources, such as computers, internet connection, and technical knowledge, anyone is able to download globally available data and perform analysis (Pfeffer & Verrest, 2016). With the growth in the technical enterprise, globally available data is proven to be more reliable, and therefore more accurate for remote analyzes at larger scales. For example, now that the Global Human Settlement Layer (GHSL) in available on Google Earth Engine (GEE), ideally national and regional authorities are able to access and utilize the data efficiently. For this paper, that transition occurred half-way through research. This was a benefit because downloading the data from European Union's website was time intensive and required advanced technical skills to extract. The switch allowed us to alter our methods and work faster.

However, there is question of globally available data correctness. Global remote sensing algorithms create a large amount of data, as seen with GHSL, but when finding conclusions at the small- to medium-sized city scale, any inconsistency with the data greatly affects results (see section 5 of chapter 2). Looking at the amount of total area covered by the spatial boundaries when completing UN Sustainable Development Goal (SDG) Indicator 11.3.1 and therefore the amount of built-up area (BUA) included in the calculations affected the calculation results. For example, in Denpasar (see section 4 of chapter 2) the 2C bounding box included BUA around the city not included in the other two boundaries. As a result, the LCRPGR ratio was almost double. If this GHSL is at all misrepresenting of BUA, the LCRPGR ratio would be different.

Locally collected data requires collaboration with local partners with particular attention to metadata, or documentation of the dataset's key components such as its quality, projection, area of coverage, and data lineage (Batcheller, 2008). When locally collected data is available, metadata is often incomplete, and the data is not updated as regularly or does not have a maintenance frequency (Batcheller, 2008). The benefit of local data is the verification of the data as it was collected by locals with local knowledge and input, increasing the quality assurance of the data and ultimately the usefulness of locally collected data for informed city planning (Tran, Shaw, Chantry, & Norton, 2009). However, utilizing the data remotely requires significant correspondence with partners at the local level if there are questions about the data. If partnership is not an option, it would be essentially impossible to work with the data if it did not have complete metadata.

Working with urban springs in Kharkiv required significant communication with partners back-and-forth. Although the partners were there to help, incomplete metadata or questions about the urban springs was not as easy to get as one would expect. In general with my experience doing research with the 2C Initiative project metadata is often incomplete. Regardless, working with the partners in Kharkiv displayed the ability of local input in locally collected data to provide a personal connection to the research that otherwise would not have been experienced remotely (see Appendix D).

Surprisingly, assessing globally available data and locally collected data lead to an additional conclusion between vector and raster datasets. GHSL and WorldPop are the globally available dataset and are rasters. The urban springs data is locally collected vector data. In order to draw more conclusive results regarding vector versus raster data, more datasets need to be considered. However, considering data for secondary cities, I conclude creating vector datasets are more conducive when collecting data locally and raster datasets provide complete, global coverage for globally available data, accessible for use as long as the city has necessary means to disseminate it.

Ultimately, reliable data for secondary cities continues to be unavailable and difficult for processing for secondary cities. Scientifically, it would be remiss to not address the limited amount datasets (three) utilized in this paper and that they may or may not be representative of all globally available data and locally collected data when drawing conclusions from the datasets compared in this thesis. However, comparing the types of data is one aspect of this research; the other is assessing geospatial data for secondary cities and city planning and development. An unavoidable truth about secondary cities is they are still data-poor, under-resourced, and lag behind in infrastructure and essential services with little to no attention at the global stage (UN-HABITAT, 2016b). With limited resources available for secondary cities, data acquisition, accuracy, and interoperability are difficult with respect to geospatial technology, Internet accessibility, and connectivity. If the globe is going to grow sustainability for future generations, attention is required of these cities.

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APPENDIX A – SDG INDICATOR 11.3.1 CALCULATIONS FOR DENPASAR, INDONESIA

Population growth rate (PGR), land consumption rate (LCR), and land consumption rate population growth rate (LCRPGR) equations for Denpasar, Indonesia. The equations calculated reflect three boundaries: local city boundary, DIVA-GIS boundary, and 2C bounding box.

Local City Boundary

$$PGR = \frac{\ln(883{,}814 / 104{,}513)}{40 \text{ yrs.}} = 0.053$$

$$LCR = \frac{\ln(79.15\text{km}^2 / 3.60\text{km}^2)}{39 \text{ yrs.}} = 0.079$$

$$LCRPGR = \frac{0.079}{0.053} = 1.49$$

DIVA-GIS Boundary

$$PGR = \frac{\ln(883{,}814 / 104{,}513)}{40 \text{ yrs.}} = 0.053$$

$$LCR = \frac{\ln(83.44\text{km}^2 / 3.68\text{km}^2)}{39 \text{ yrs.}} = 0.80$$

$$LCRPGR = \frac{0.080}{0.053} = 1.50$$

2C Bounding Box

$$PGR = \frac{\ln(883{,}814 / 104{,}513)}{40 \text{ yrs.}} = 0.053$$

$$LCR = \frac{\ln(174.30\text{km}^2 / 8.37\text{km}^2)}{39 \text{ yrs.}} = 0.078$$

$$LCRPGR = \frac{0.078}{0.053} = 1.46$$

APPENDIX B – SDG INDICATOR 11.3.1 CALCULATIONS FOR MEKELLE, ETHIOPIA

Population growth rate (PGR), land consumption rate (LCR), and land consumption rate population growth rate (LCRPGR) equations for Mekelle, Ethiopia. The equations calculated reflect three boundaries: local city boundary, DIVA-GIS boundary, and 2C bounding box.

Mekelle

Local City Boundary

$$\text{PGR} = \frac{\ln(440{,}042 / 41{,}883)}{40 \text{ yrs.}} = 0.059$$

$$\text{LCR} = \frac{\ln(9.39\text{km}^2 / 0.19\text{km}^2)}{39 \text{ yrs.}} = 0.100$$

$$\text{LCRPGR} = \frac{0.100}{0.059} = 1.70$$

DIVA-GIS Boundary

$$\text{PGR} = \frac{\ln(440{,}042 / 41{,}883)}{40 \text{ yrs.}} = 0.059$$

$$\text{LCR} = \frac{\ln(4.77\text{km}^2 / 0.02\text{km}^2)}{39 \text{ yrs.}} = 0.137$$

$$\text{LCRPGR} = \frac{0.137}{0.059} = 2.32$$

2C Bounding Box

$$\text{PGR} = \frac{\ln(440{,}042 / 41{,}883)}{40 \text{ yrs.}} = 0.059$$

$$\text{LCR} = \frac{\ln(9.45\text{km}^2 / 0.21\text{km}^2)}{39 \text{ yrs.}} = 0.098$$

$$\text{LCRPGR} = \frac{0.098}{0.059} = 1.67$$

APPENDIX C – SDG INDICATOR 11.3.1 CALCULATIONS FOR KHARKIV, UKRAINE

Population growth rate (PGR), land consumption rate (LCR), and land consumption rate population growth rate (LCRPGR) equations for Kharkiv, Ukraine. The equations calculated reflect three boundaries: local city boundary, DIVA-GIS boundary, and 2C bounding box.

Local City Boundary

$$PGR = \frac{\ln(1{,}442{,}204 / 1{,}352{,}608)}{40 \text{ yrs.}} = 0.0016$$

$$LCR = \frac{\ln(299.19\text{km}^2 / 194.50\text{km}^2)}{39 \text{ yrs.}} = 0.011$$

$$LCRPGR = \frac{0.011}{0.0016} = 6.89$$

DIVA-GIS Boundary

$$PGR = \frac{\ln(1{,}442{,}204 / 1{,}352{,}608)}{40 \text{ yrs.}} = 0.0016$$

$$LCR = \frac{\ln(261.67\text{km}^2 / 176.12\text{km}^2)}{39 \text{ yrs.}} = 0.010$$

$$LCRPGR = \frac{0.010}{0.0016} = 6.33$$

2C Bounding Box

$$PGR = \frac{\ln(1{,}442{,}204 / 1{,}352{,}608)}{40 \text{ yrs.}} = 0.0016$$

$$LCR = \frac{\ln(446.49\text{km}^2 / 241.79\text{km}^2)}{39 \text{ yrs.}} = 0.016$$

$$LCRPGR = \frac{0.016}{0.0016} = 9.81$$

APPENDIX D – URBAN SPRING PHOTGRAPHS IN KHARKIV, UKRAINE

Photographs of urban springs taken by Secondary City (2C) Initiative partners in Kharkiv, Ukraine. The seven photographs display the diversity of aesthetic functions and resources a spring may have. Listed with the photograph is the Spring identification number and the location of the spring. The Spring identification numbers correlate to the locations and discharge amounts in chapter 4 (Figure 3.1 and Table 3.6). All photograph rights are reserved to the 2C Initiative and Kharkiv team.

Spring 16 is more centrally located and to the east. Spring 16 has five spouts and amusing statue.

Spring 2 located toward the southwest side of the city. The spring has three spouts and mural for visual enjoyment.


Spring 23 is located on the east side of the city.

Spring 24 is located at the northeastern part of Kharkiv.