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Article

A Geospatial Cyberinfrastructure for Urban Economic Analysis and Spatial Decision-Making

Wenwen Li [1,]*, Linna Li [2], Michael F. Goodchild [2] and Luc Anselin [1]

[1] GeoDa Center for Geospatial Analysis and Computation, School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ 85287, USA; E-Mail: luc.anselin@asu.edu

[2] Center for Spatial Studies, Department of Geography, University of California, Santa Barbara, CA 93106, USA; E-Mails: linna@geog.ucsb.edu (L.L.); good@geog.ucsb.edu (M.F.G.)

***** Author to whom correspondence should be addressed; E-Mail: wenwen@asu.edu; Tel.: +1-480-727-5987; Fax: +1-480-965-8313.

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Abstract: Urban economic modeling and effective spatial planning are critical tools towards achieving urban sustainability. However, in practice, many technical obstacles, such as information islands, poor documentation of data and lack of software platforms to facilitate virtual collaboration, are challenging the effectiveness of decision-making processes. In this paper, we report on our efforts to design and develop a geospatial cyberinfrastructure (GCI) for urban economic analysis and simulation. This GCI provides an operational graphic user interface, built upon a service-oriented architecture to allow (1) widespread sharing and seamless integration of distributed geospatial data; (2) an effective way to address the uncertainty and positional errors encountered in fusing data from diverse sources; (3) the decomposition of complex planning questions into atomic spatial analysis tasks and the generation of a web service chain to tackle such complex problems; and (4) capturing and representing provenance of geospatial data to trace its flow in the modeling task. The Greater Los Angeles Region serves as the test bed. We expect this work to contribute to effective spatial policy analysis and decision-making through the adoption of advanced GCI and to broaden the application coverage of GCI to include urban economic simulations.

Keywords: cyberinfrastructure; conflation; OGC; WPS; WMS; WFS; provenance; spatial decision support (SDS); service chaining; urban economic simulation

1. Introduction

Urban areas, as characterized by very high population density and vast human activities, are where over 50% of the world's population lives and where over 75% of the world's energy is used [1]. This proportion is only expected to continue increasing as the 21st Century continues. The rapid growth of population in urban areas raises serious concerns about whether this growth can be sustained without severely compromising quality of life. One determining factor is how well policy issues are addressed with quality economic analysis to support practical policy formulation. Providing specific and useful answers to policy questions requires complex analysis, since environment, energy, land use, housing and transit infrastructure are not isolated economic subsystems, but instead interact with feedbacks. Modeling the interactions between and within these subsystems is necessary in order to understand how specific policies and plans work. For example, when a policy bearing on the transit system is studied using a transportation model in isolation, it may show well-defined impacts, but when all subsystems, such as land use, environment, housing and regional economy, are considered together, a more accurate and complete picture of benefits and costs will emerge.

In practice, urban planning and policy-making have become increasingly complex, due to the dynamics raised through the urbanization process [2,3], asymmetric development in spatial planning [4] and the rise of big urban data [5]. Meanwhile, many technical obstacles have been challenging the effectiveness in the decision-making process. First, different types of geospatial resources are scattered across government agencies, public and private sectors. There is limited coordination and inadequate timely adoption of advanced technologies to share these resources, leading to the problem of an "information island" [6]. Second, the available data are poorly documented, making it difficult if not infeasible for researchers to understand their lineage and content and to make sound judgment about their applicability for a specific problem. Third, the data are typically produced using local standards with respect to format, metadata structure, *etc.*, resulting in a high degree of heterogeneity and, thus, hampering the goal of achieving geospatial interoperability [7]. Fourth, failures in open collaboration lead to duplicate efforts in the development of software to analyze and process geospatial data.

Geospatial cyberinfrastructure (GCI), which integrates computer hardware, software, communication networks, data and human resources into a seamless whole, provides a software platform to allow complex system modeling and the integration of distributed scientific data [8,9]. The GCI represents a movement away from the stand-alone desktop paradigm to a virtual web service-based framework in which computation is carried out in the cloud rather than tied to a specific terminal computer [10]. The implementation of a GCI focuses on improving interoperability of distributed geospatial resources [11]. It promotes widespread sharing of geospatial data and analytical functionalities based upon a service-oriented architecture [12] and empowers data-driven scientific analysis in an open and collaborative fashion [13]. In this vein, the GCI provides a promising solution framework to address several technical challenges encountered in the domain of urban economic modeling.

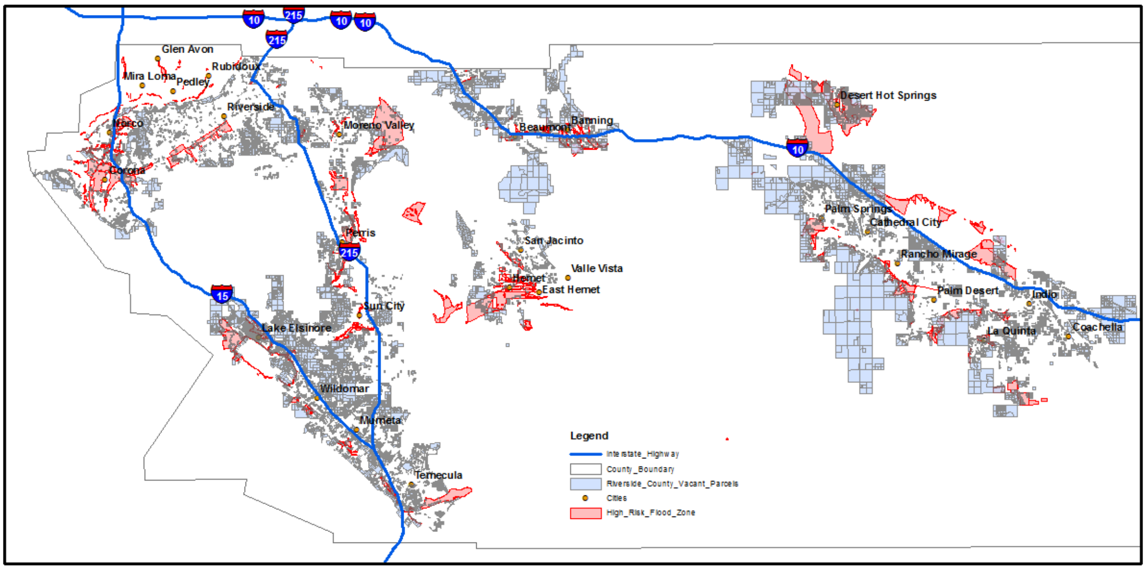
In this paper, we report our findings based on our efforts to design and develop an urban GCI for effective policy analysis and decision-making. We found that moving spatial analytical tools to cyberspace and providing adequate provenance information greatly facilitates the collaborative decision-making process. This GCI is built upon a service-oriented architecture that allows (1) widespread sharing and seamless integration of distributed geospatial data; (2) an effective way to address the uncertainty and positioning errors introduced by fusing data from diverse sources; (3) the decomposition of complex planning questions into atomic spatial analysis tasks and the generation of a web service chain to tackle such complex problems; and (4) capturing and representing provenance of geospatial data to trace its flow in the modeling task. The Greater Los Angeles Region (LA County, Ventura County, San Bernardino County, Riverside County, Imperial County and Orange County), which is one of the most populous regions in the US, serves as our study area.

The rest of the paper is organized as follows: Section 2 describes a planning use case that requires advanced cyber-technologies to address challenges in effective decision-making. Section 3 reviews related work in the literature. Section 4 proposes three advanced techniques, including optimized conflation of multi-source data, composition of geoprocessing services to tackle complex spatial analysis tasks and data provenance to trace the flow of data through processing. Section 5 introduces the software architecture and the graphic user interface of the urban GCI, and Section 6 concludes the paper and discusses further research directions.

2. Planning Use Case

Rapid population growth in a region, such as the greater Los Angeles region, our study area, creates pressures on the economy, environment and transportation systems, among other factors. Urban planners are tasked to manage this growth and take into account multiple objectives and constraints in developing future plans. For example, when an urban planner needs to make decisions on which parcels are suitable for development, a set of environmental and infrastructural constraints must be taken into consideration. For instance, there should be no construction on the 50-year flood zones of high-risk. Figure 1 shows an overlay of the distribution of vacant land parcels and flood zone data in Riverside County, a subset of the study area. To support spatial analysis and practical decision-making, a number of Geographic Information System (GIS) operations need to be conducted in sequence: (1) subset the parcel database to retrieve all parcels in the study area; (2) filter out parcels that are not vacant; (3) retrieve flood zone data covering the study area; and (4) overlay vacant parcel data with the flood zone data to generate a map of potential development sites. When accessibility factors, such as the distance between a parcel and its nearest highway entrance, are considered, more comprehensive network-based analysis is needed, such as (1) data preprocessing to conflate GIS data from disparate sources to ensure high accuracy and (2) shortest path identification from potential residential housing sites to highway entrances. Land use and transportation planners need such information to make comprehensive plans to meet the goal of sustainable development. Three key research questions arise in cyber-enabling such a system: (1) How to implement information integration from multiple sources at the actual data level? (2) How to implement seamless interoperation among heterogeneous datasets and develop a standard interface to data and analytical tools? (3) How to provide effective provenance to trace the origin of data and its movement among databases?

Figure 1. Distribution of vacant land and high-risk flood zones of Riverside County in the greater LA region.



3. Literature

Since its emergence in the late 1990s, cyberinfrastructure has increasingly played a role in advancing a number of fields, such as particle physics, system biology and GIS [14]. In this respect, four major aspects of the cyberinfrastructure (CI) are important: providing access to data, integrating disparate data sources, service chaining and provenance. We briefly review each in turn.

A growing body of research literature exists concerning data sharing [15] and the establishment of geoportals [16–18]. However, in practice, much work is still needed to improve the technical design and long-term viability of a geoportal implementation [19]. Some recent examples of ongoing efforts include the National Carbon Sequestration Database and Geographic Information System (NATCARB), the first national cyberinfrastructure for carbon capture and storage (CCS). The NATCARB portal provides an online tool to visualize disparate data and perform web-based analysis, such as pipeline measurement, cost estimation, *etc.*, on carbon sequestration. A related example pertains to the Arctic research community, where efforts have been made to efficiently discover, integrate and visualize relevant data and web services in order to facilitate Arctic environmental research [20]. In addition, geolibraries, such as the Alexandria Digital Library (http://www.alexandria.ucsb.edu/), were established to provide distributed library services for georeferenced data [21].

One of the functionalities of CI-enabled geoportals is to find and integrate disparate geographic data. However, this is still limited in that the focus is on providing simple access to different data sources or to visual overlay of different layers. The data themselves are not conflated into a consistent data structure. Therefore, heterogeneous geographic data cannot be used directly for further analysis, because the same location in different sources may correspond to different locations on the Earth's surface. Conflation, a technique that deals with resolving discrepancies between different sources, is a solution to this problem [22,23]. The most challenging task in data conflation is feature matching, which relies on a similarity measurement to decide the correspondence between two features. Various similarity metrics have been developed, based on geometry, attribute and topology [22,24,25]. After a similarity measurement is defined, most methods use a greedy strategy to find matched pairs of geographic features in a sequential manner. One major problem with this strategy is that a matching mistake in a previous step leads to more errors in later stages. The conflation method we use for data integration in this urban GCI adopts an optimization method [26] that overcomes the shortcomings of the greedy strategy by taking into consideration the total similarity of all corresponding pairs simultaneously, thus resulting in a higher percentage of correct matches and a general improvement of data quality.

Once the data quality is ensured, geoportals tend to rely on Web Map Service (WMS), the most widely used OGC (Open Geospatial Consortium) protocol [27–30]. However, WMS lacks the capability to query individual geographic features and to perform spatial analysis and, therefore, is not suitable for carrying intermediate results throughout a web service chain. Alameh [31] conducted a pilot study to discuss the possibility of chaining OGC web services and reviewed a number of communication protocols (Web Service Description Language WSDL; Universal Description, Discovery and Integration UDDI; Simple Object Access Protocol SOAP, *etc.*) that could be adopted to facilitate the execution of web services. Yue *et al.* [32] proposed a conceptual model for composite geospatial analytical services by extending ebRIM (ebXML Registry Information Model). However, no implementation details were revealed. As a backend support to our GCI, the OGC Web Feature Service (WFS) and OGC Web Processing Service (WPS) are enabled for interaction with individual features and decomposition of a complex spatial task into subprocesses using service chaining [20].

Another component that is missing in existing geoportals is provenance. Provenance, also known as lineage, records the origins of data and procedures performed on the data as they are shared and analyzed. In the 1990s, a conceptual design of GIS with the capability to record provenance was proposed to document data sources, data transformations and intermediate and final data products [33]. Since then, a number of methods to capture provenance have been proposed in the geospatial domain [34–39], but little research has been done in the context of a service-oriented environment. In contrast to the desktop environment, a service-oriented architecture combines distributed data and loosely coupled web services to conduct scientific study or to provide decision support [32,40]. Our GCI portal for urban economic analysis and simulation presents a way to generate standardized provenance information based on W3C PROV.

4. Methodology

4.1. Conflation

Accurate data are a foundation for the urban GCI. First, the urban GCI serves as a data portal for browsing and downloading data that are relevant for regional economic analysis and decision-making. Usually, such a process requires separate data for different aspects of the study area, such as land use and transportation. Different geographic data layers are overlaid based on spatial location, so good spatial accuracy is desirable. Second, adequate attribute data are required for spatial analysis and policy-making. The central model of this GCI is a regional economy, land use and transportation model, which requires land use data, transportation data, trip data, and so on, as input. No single source satisfies our data needs. For example, land use data and trip data are provided by the Southern

California Association of Governments (SCAG) and US Department of Transportation, respectively. Even for the same themes, such as road networks, one single data source does not meet both spatial and attribute quality standards. High spatial accuracy is critical for integrating road networks with other data layers. On the other hand, attributes of road networks, including speed limit and road category, are required to run the model. Since required information is not provided by a single data source, we integrated road networks from two data sources using geographic data conflation.

Geographic data conflation is a process of integrating data from multiple sources in order to generate a new dataset with improved spatial and attribute accuracies. There are two major components in geographic data conflation: feature matching and feature transformation [23]. Feature matching refers to the process of finding two features in different datasets that represent the same entity in reality. The criterion for determination of two corresponding geographic features is usually a similarity measurement that characterizes the important aspects of a feature, such as location, geometry, topology and attribute information. After two features are matched, the resultant feature in a conflated dataset can be generated by transforming the two original datasets, such as through integration of relevant attributes and adjustment of spatial locations.

In our use case, we need both high spatial accuracy and adequate attributes for roads. Two data sources of road networks were used: road networks provided by SCAG and the TIGER (Topologically Integrated Geographic Encoding and Referencing) files provided by the US Census Bureau. Data from SCAG contain many valuable attributes, including speed limit and road capacity, while the TIGER data have minor roads that are not available in the SCAG data and have better spatial accuracy. As shown in Figure 2, the geographic location and shape are better aligned with the true location of the feature in the TIGER map. In addition, some minor roads represented in the TIGER file are not represented in the SCAG data. The two datasets were conflated to provide a more complete and accurate representation of the road networks in the study area.

Figure 2. The discrepancy between Southern California Association of Governments (SCAG) data (red) and Topologically Integrated Geographic Encoding and Referencing (TIGER) data (blue).

To achieve data conflation, the first critical step is feature matching between the two datasets using an optimized polyline feature matching strategy [41]. The matching process is formulated as an adapted assignment problem, whose objective is to maximize the total similarity between all matched pairs in the two datasets. The feature matching can be formulated as the following objective function:

$$Maximize\ \sum_{i=1}^{p}\sum_{j=1}^{q} s_{i->j} z_{i->j} \tag{1}$$

$$z_{i->j} = \begin{cases} 1, & \text{if } a \text{ match is made from feature } i \text{ to feature } j \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where p and q indicate the number of geographic features in the first and second datasets, respectively, i and j are the indices for geographic features in the two datasets, $S_{i\rightarrow j}$ is the similarity from feature i to feature j and $z_{i\rightarrow j}$ is used to record a match between two features. The similarity from feature i to feature j $S_{i\rightarrow j}$ is a combination of directed Hausdorff distance and the dissimilarity between two feature names, calculated based on the following equation:

$$s_{i->j} = \begin{cases} 0, & \text{if } d_{i->j}^{DH} > a \\ a - d_{i->j}^{DH} & \text{if } d_{i->j}^{DH} < a \text{ and } D_{ij}^{n} \text{ is not available} \\ a - (D_{ij}^{n} + d_{i->j}^{DH})/2 & \text{if } d_{i->j}^{DH} < a \text{ and } D_{ij}^{n} \text{ is available} \end{cases} \tag{3}$$

where $d_{i\rightarrow j}^{DH}$ is the directed Hausdorff distance from feature i to feature j, D_{ij}^{n} is the dissimilarity between two feature names and a is a threshold beyond which two features are considered too far apart to be matched. The equations for calculating $d_{i\rightarrow j}^{DH}$ and D_{ij}^{n} are as follows:

$$d_{i->j}^{DH} = \max_{x\in L_i}\{d(x, L_j)\} \tag{4}$$

$$D_{ij}^{n} = \frac{2D_{ij}^{h}}{L_i + L_j} \times \alpha \tag{5}$$

where $d(x, L_j) = \min\{d(x, y) : y \in L_j\}$ is the shortest distance between a point, x, on feature i and feature j, D_{ij}^{h} is the Hamming distance between the names of feature i and feature j, L_i and L_j are the lengths of two feature names and α is a factor to normalize the name dissimilarity, so it is comparable with the directed Hausdorff distance, $d_{i\rightarrow j}^{DH}$, when they are combined. The solution to the objective function (1) generates a matrix of $z_{i\rightarrow j}$, which gives all matched pairs of the features.

The advantage of such an optimization method is that errors made in a previous stage of a greedy strategy may be corrected by simultaneously considering all matched pairs of features. This matching method is particularly effective for polyline features, such as road networks, because it incorporates a directed Hausdorff distance into the similarity measurement to address part-and-whole correspondences. After corresponding features are matched in the two datasets, the spatial location of the roads in the TIGER dataset is preserved, due to its higher accuracy and better coverage, and the attributes of the matched features in the SCAG dataset are transferred to the corresponding features in the other dataset. As a result, we obtain a road network dataset that retains both good spatial and attribute information for data overlay, query and analysis.

4.2. Service Chain of Geospatial Processes in the Service-Oriented GCI

Conflation ensures the quality of GIS data used for modeling the land use, transportation and housing for regional economic analysis in the study area. The next question is how to openly share these heterogeneous resources across the geographically distributed team, how to assure a smooth flow of data in the application of complex spatial analysis procedures and how to automate this process in such a way that policy makers with limited GIS expertise can freely execute different scenarios and get timely answers in an intuitive manner.

The Open Geospatial Consortium (OGC), which aims to develop community-consensus open geospatial standards, provides a family of enabling technologies for sharing geospatial data and analytical capabilities on a distributed network. To support sharing of geospatial data hosted in the urban GCI, two types of data services are developed, Web Map Services (WMS) and Web Feature Services (WFS). WMS [42] interacts with clients through HTTP requests and returns geo-referenced static images in the region of interest (ROI). As WMS does not return the actual data, but a map rendered from the data, it is mainly used for visualizing results of a spatial analysis. A WFS [43] was developed mainly for the purpose of exchanging actual feature data rather than visual display. The raw GIS shapefiles are encoded into an intermediate format GML (Geographic Markup Language) [44]—a geo-enhanced version of XML (eXtensive Markup Language). A WFS (version 1.1.0) defines up to twelve operations, of which the most commonly used are "GetCapabilities", "DescribeFeatureType" and "GetFeature". "GetCapabilities" generates a metadata document describing the WFS, as well as supported WFS operations. "DescribeFeatureType" returns a description of feature types (Point, Polyline or Polygon) supported by a WFS service. "GetFeature" returns the actual data encoded in GML for heterogeneous data interoperation from multiple sources.

In addition to data services, the urban GCI also implements a Web Processing Service (WPS), in order to facilitate sharing, discovery and dynamic binding of geospatial processes. The concept of WPS realizes a paradigm shift from service providing data, such as the aforementioned WMS and WFS, to service providing information [45,46]. Therefore, it fits the goal of generic CI in maximizing the reuse of existing analytical tools, as well as the goal of our urban GCI to tackle complex policy questions into chained workflows of geospatial operations. A WPS supports three standardized web requests: "GetCapabilities", "DescribeProcess" and "Execute". "GetCapabilities" returns the metadata that describe a processing service, including the service provider and online geoprocesses it supports. Once a geoprocess of interest is identified, the "DescribeProcess" can be invoked to get the definitions of a geoprocess. These definitions include functional descriptions about the process, input/output and supported data formats for input/output. Once the input data are organized into desired formats, a GET/POST "Execute" request can be sent to the GCI portal's WPS server. An important feature of our WPS implementation is its ability to support subprocesses, in the sense that the input of one WPS process can come from the output of another WPS process. This feature enables service chaining for tackling complex processes by carrying out a sequence of subprocesses. In our WPS implementation, WFS/GML is used to transfer data between different processing services.

Following the scenario given in Figure 1, our GCI portal gets a request to estimate the total developable land area for Riverside County's planning department. First, the "developable land area" must be defined. A developable area should satisfy two constraints: its land use type is vacant and the land is not within an area with a 2% annual chance of flooding and additional hazards associated with storm waves. Land use classifications (residential, industrial, commercial, vacant, *etc.*) are recorded in the SCAG parcel database, and the parcel data are hosted as a WFS in our urban GCI portal. The raw flood zone data in Esri shapefile format can be retrieved from FEMA (Federal Emergency Management Agency) and are published as WFS. In order to obtain all vacant land parcels, a "Filter" operation, which extracts parcel records by its land use type "vacant" needs to be performed on top of the WFS "GetFeature" request. Figure 3 demonstrates the example request in XML. The 50-year flood plain data for Riverside County can be obtained in a similar fashion. The resulting dataset is encoded in GML for multi-source data interoperation.

Figure 3. A sample Web Feature Service (WFS) "GetFeature" request to subset SCAG parcel dataset to obtain all records of vacant land in Riverside County. The first filter condition "PropertyIsEqualTo" returns all parcel polygons with land use type vacant (land use code is: "3000" and field name is: "LU08"). The second filter condition returns parcel polygons belonging to Riverside County only.

```
<wfs:GetFeature xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
        xsi:schemaLocation="http://www.opengis.net/wfs
http://localhost:9090/geoserver/schemas/wfs/1.0.0/WFS-basic.xsd"
        xmlns:gml="http://www.opengis.net/gml" xmlns:wfs="http://www.opengis.net/wfs"
        xmlns:ogc="http://www.opengis.net/ogc"        service="WFS"        version="1.0.0"
outputFormat="text/xml; subtype=gml/3.2">
        <wfs:Query typeName="mrpi:SCAGparcel"
                xmlns:mrpi="http://localhost/ows/featuretype">
                <ogc:Filter xmlns="http://www.opengis.net/ogc">
                <ogc:PropertyIsEqualTo>
                        <ogc:PropertyName>LU08</ogc:PropertyName>
                        <ogc:Literal>3000</ogc:Literal>
                </ogc:PropertyIsEqualTo>
                <ogc:PropertyIsEqualTo>
                        <ogc:PropertyName>County</ogc:PropertyName>
                        <ogc:Literal>Riverside</ogc:Literal>
                </ogc:PropertyIsEqualTo>
                </ogc:Filter>
        </wfs:Query>
</wfs:GetFeature>
```

Once the datasets are prepared and made interoperable through WFS/GML, a nested processing service is orchestrated to tackle the given problem. Figure 4 shows a complete chart of data flows through multiple processing services in sequence. Briefly, in order to calculate the total developable area, the WPS process "GetGeometryArea" is needed. This process takes a projected polygon as input and returns the polygon area in numerical value (the same unit as the input data). Therefore, the developable parcel polygons generated from previous steps must be consolidated into a multi-part polygon. To fit the right type of data into the "GetGeometryArea" process, a subprocess "CollectGeometryFeatures", (a WPS), is launched to take in data representing multiple developable parcels and output one multi-part polygon. As discussed earlier, the developable parcels are the parcels that are vacant and not within the high-risk flood zones. This dataset is generated by taking the spatial differences of geometries that are in Set 1 (the vacant parcels) and Set 2 (the floodplain zones) by a processing service called “Difference”. Both sets of data are encoded in GML and are subsets of original raw data from two heterogeneous sources: SCAG parcel database and FEMA Esri shapefile. Figure 5 shows the XML-encoded WPS request that implements the entire chain of data/processing services illustrated in Figure 4. The desired response gives an answer for the total developable area in Riverside County as 334.97 square miles.

Figure 4. Workflow chart of chained geoprocessing.

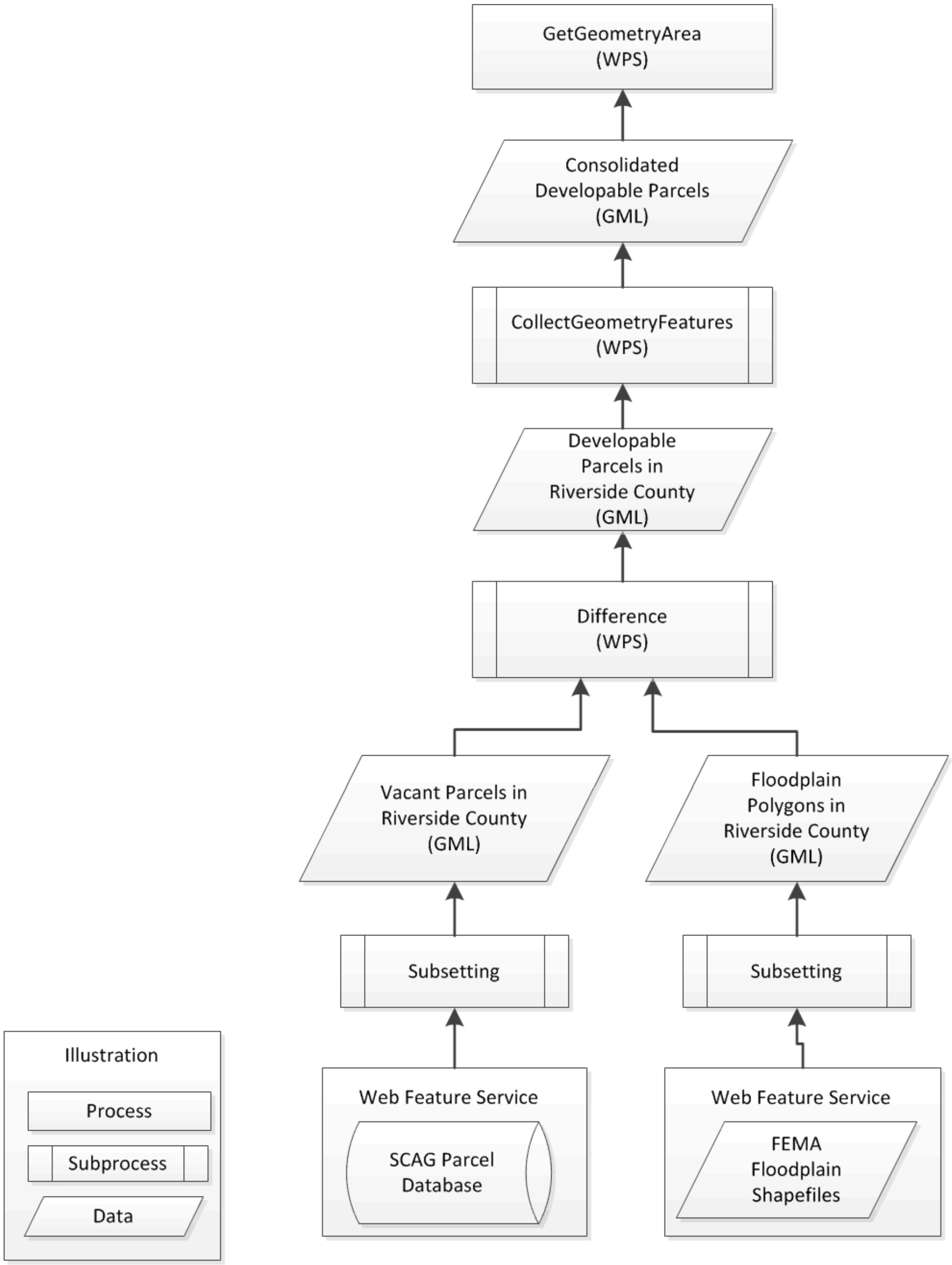


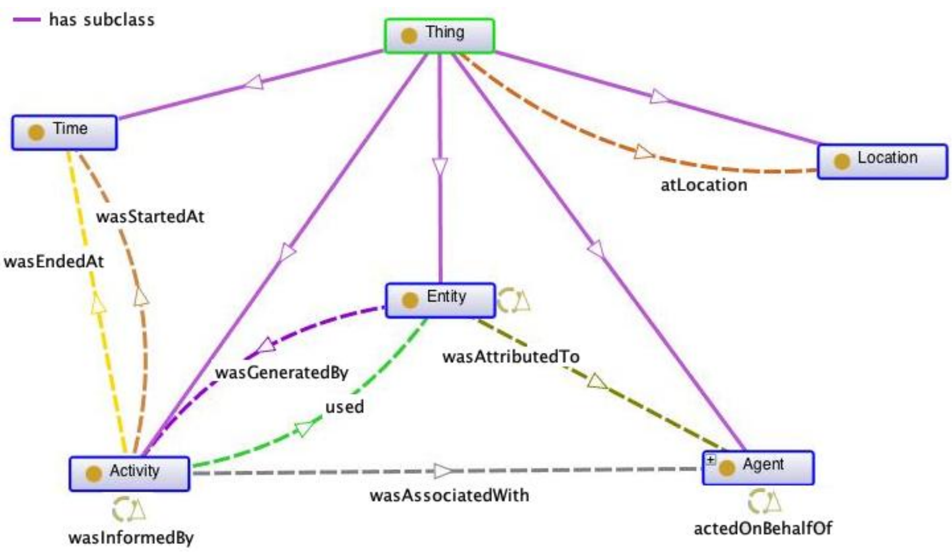
Figure 5. The nested WPS request in XML to answer the question about total developable land area in Riverside County, CA.


```
<?xml   version="1.0"   encoding="UTF-8"?><wps:Execute   version="1.0.0"   service="WPS"
xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
xmlns="http://www.opengis.net/wps/1.0.0"          xmlns:wfs="http://www.opengis.net/wfs"
xmlns:wps="http://www.opengis.net/wps/1.0.0"  xmlns:ows="http://www.opengis.net/ows/1.1"
xmlns:gml="http://www.opengis.net/gml"           xmlns:ogc="http://www.opengis.net/ogc"
xmlns:wcs="http://www.opengis.net/wcs/1.1.1"  xmlns:xlink="http://www.w3.org/1999/xlink"
xsi:schemaLocation="http://www.opengis.net/wps/1.0.0
http://schemas.opengis.net/wps/1.0.0/wpsAll.xsd">
 <ows:Identifier>JTS:area</ows:Identifier>
 <wps:DataInputs>
  <wps:Input>
   <ows:Identifier>geom</ows:Identifier>
   <wps:Reference                 mimeType="text/xml;                  subtype=gml/3.1.1"
xlink:href="http://localhost/wps" method="POST">
    <wps:Body>
     <wps:Execute version="1.0.0" service="WPS">
      <ows:Identifier>gs:CollectGeometryFeatures</ows:Identifier>
      <wps:DataInputs>
       <wps:Input>
        <ows:Identifier>features</ows:Identifier>
        <wps:Reference       mimeType="text/xml"       xlink:href="http://geoserver/wps"
method="POST">
         <wps:Body>
          <wps:Execute version="1.0.0" service="WPS">
           <ows:Identifier>JTS:difference</ows:Identifier>
           <wps:DataInputs>
            <wps:Input>
             <ows:Identifier>a</ows:Identifier>
             <wps:Reference             mimeType="text/xml;            subtype=gml/3.1.1"
xlink:href="http://localhost/ows/ows?service=wfs&amp;request=GetFeature&amp;typename=mrp
i:SCAGparcel&amp;filter=<ogc:Filter
xmlns="http://www.opengis.net/ogc"><ogc:PropertyIsEqualTo><ogc:PropertyName>LU08</ogc:Pr
opertyName><ogc:Literal>3000</ogc:Literal></ogc:PropertyIsEqualTo><ogc:PropertyIsEqualTo
><ogc:PropertyName>County</ogc:PropertyName><ogc:Literal>Riverside</ogc:Literal></ogc:Pr
opertyIsEqualTo></ogc:Filter>" method="GET"/>
            </wps:Input>
            <wps:Input>
             <ows:Identifier>b</ows:Identifier>
             <wps:Reference             mimeType="text/xml;            subtype=gml/3.1.1"
xlink:href="http://localhost/ows/ows?service=wfs&amp;request=GetFeature&amp;typename=mrp
i:floodplain&amp;filter=<ogc:Filter
xmlns="http://www.opengis.net/ogc"><ogc:PropertyIsEqualTo><ogc:PropertyName>County</ogc:
PropertyName><ogc:Literal>Riverside</ogc:Literal></ogc:PropertyIsEqualTo></ogc:Filter>"
method="GET"/>
            </wps:Input>
           </wps:DataInputs>
           <wps:ResponseForm>
            <wps:RawDataOutput mimeType="text/xml; subtype=gml/3.1.1">
             <ows:Identifier>result</ows:Identifier>
            </wps:RawDataOutput>
           </wps:ResponseForm>
          </wps:Execute>
         </wps:Body>
        </wps:Reference>
       </wps:Input>
      </wps:DataInputs>
      <wps:ResponseForm>
       <wps:RawDataOutput mimeType="text/xml; subtype=gml/3.1.1">
        <ows:Identifier>result</ows:Identifier>
       </wps:RawDataOutput>
      </wps:ResponseForm>
     </wps:Execute>
    </wps:Body>
   </wps:Reference>
  </wps:Input>
 </wps:DataInputs>
 <wps:ResponseForm>
  <wps:RawDataOutput>
   <ows:Identifier>result</ows:Identifier>
  </wps:RawDataOutput>
 </wps:ResponseForm>
 </wps:Execute>
```


4.3. Data and Analytic Provenance

In addition to automated data conflation and service composition, a third feature of our urban GCI is its ability to trace the source and flow of data throughout the process of complex geospatial analysis until it enters the database. This information is also called provenance data/information. The provenance information is of great importance for a distributed team to gain (1) a common understanding of the content of data and how the data can be used; (2) an assessment of datasets to decide if they meet the requirements (on data quality, accuracy, timeliness, *etc.*) for specific applications; (3) a way to acknowledge the producer of the data; and (4) replicability of a dataset. Figure 6 demonstrates the conceptual provenance model built upon W3C PROV (http://www.w3.org/TR/2011/WD-prov-dm-20111018/). Five main classes (Activity, Entity, Agent, Time and Location) are defined. All of these classes are inherited from a superclass "Thing". "Activity" refers to the procedure followed to generate a dataset. "Subset", "Difference", "CollectGeomtryFeatures" and "Area", described in Figure 4, are objects of "Activity". An "Entity", in general, can be viewed as a type of "Thing" with some fixed aspects. This could be a physical entity (such as a hard drive), a digital entity (a dataset) or a conceptual element (such as the model demonstrated in Figure 6). By definition, an entity may be real or imagery, but in the context of our work, an entity refers mainly to a digital object, such as a dataset, a document or a software tool. "Agent" is responsible for an activity to take place, for an entity to be generated or for another agent's activity. An agent could be an organization (such as SCAG), a person or a software agent. Two additional nodes "Time" and "Location" are also included in this model to define the spatiotemporal dimensions of provenance information.

Figure 6. Conceptual model of W3C provenance ontology.



The interrelationship (arrows in Figure 6) among "Activity", "Agent" and "Entity" indicate that an activity uses one or more entities to generate a new entity or update an existing entity. One activity can be informed or invoked by another activity, such as calling a subprocess WPS in the main WPS thread. An activity is associated with an agent or an organization. The agent can conduct an activity on behalf of another agent. An activity instance is directly associated with a "Time" node, which defines the start and end time of this activity. This could also describe the time when an entity is generated. Each entity belongs to an agent, which is responsible for performing an activity. Each of the three classes can be associated with node "Location", indicating where an agent is physically located, where an entity is stored or where an activity takes place.

The conceptual provenance model can be further developed to build a provenance ontology. This supports a standardized representation of provenance information and the integration of multi-source ontologies. Figure 7 demonstrates a provenance ontology (PROV-O) recording the process of how the developable land parcels are obtained. Three namespaces, XSD, FOAF and PROV, are imported. XSD is the XML schema defining the rules to examine the validity of an XML document, in which the provenance is encoded. FOAF defines schema for describing people and the links between them. It is used to describe a human "agent", who is responsible for some activities. PROV is the W3C provenance standards, defining classes of "Activity", "Entity", "Agent" and interrelationships among them. The PROV-O fragment is encoded in Terse RDF Triple Language (Turtle). This standardized encoding of provenance information not only allows recording the steps of how data is derived, but also supports the interchange of provenance in our GCI portal with other systems. Additionally, replication of datasets is enabled by following the lineage and processing flow defined in the provenance ontology.

Figure 7. An example PROV ontology tracing the generation of developable land parcels in Riverside County.

```
@prefix xsd:  <http://www.w3.org/2001/XMLSchema#> .
@prefix foaf: <http://xmlns.com/foaf/0.1/> .
@prefix prov: <http://www.w3.org/ns/prov#> .
@prefix :     <http://www.asu.edu#> .

:developableLandInRiversideCA
   a prov:Entity;
   prov:wasGeneratedBy  : spatialDifferenceActivity;
   prov:wasDerivedFrom  : parcelEntity,floodplainEntity;
   prov:wasAttributedTo :Li;
.

:Li
   a foaf:Person, prov:Agent;
   foaf:mbox            <mailto:wenwen@asu.edu>;
   prov:actedOnBehalfOf :asu,ucsb;
.

:asu
   a foaf:Organization, prov:Agent;
   foaf:name "Arizona State University";
.

: spatialDifferenceActivity
   a prov:Activity;
   prov:used              :parcelEntity, floodplainEntity;
   prov:wasAssociatedWith :Li;
   prov:wasStartedAt      :"2013-01-20T01:30:00Z"^^xsd:dateTime
   prov:wasStartedAt      :"2013-01-20T04:30:00Z"^^xsd:dateTime
.

: parcelEntity
   a prov:Entity;
   prov:wasGeneratedBy  :subsetActivity;
   prov:wasDerivedFrom  :SCAGparcelData;
   prov:wasAttributedTo :Li;
   prov:wasInformedBy   : spatialDifferenceActivity;
.

: floodplainEntity
   a prov:Entity;
   prov:wasGeneratedBy  :subsetActivity;
   prov:wasDerivedFrom  :FEMAfloodplainData;
   prov:wasAttributedTo :Li;
   prov:wasInformedBy   : spatialDifferenceActivity;
.

: SCAGparcelData
   a prov:Entity;
   prov:wasAttributedTo :SCAG;
   prov:spatialDataQuality: 0.5m;
.

:government a foaf:Organization, prov:Agent .
```

5. System Architecture of Urban GCI and Prototypes

Figure 8 demonstrates the system architecture of our urban GCI portal. First, all datasets, including road network, floor space, land use, *etc.*, and their provenance are stored in the geospatial database PostGreSQL (module a). They are published through an open source package Geoserver (http://www.geoserver.org) into both OGC Web Map Services (WMS) and Web Feature Services (WFSs) for resource integration purposes (module c). Specifically, WMSs are mainly used for client-side visualization and interoperation of data in various formats; whereas WFSs, carrying the actual geometries of raw data in a GML format, are used for transferring intermediate results through a sequence of geospatial processes. These geospatial processes (module b), including buffer, intersection, area, *etc.*, supported by the JTS Topology Suite (http://tsusiatsoftware.net/jts/main.html) are published into standard OGC Web Processing Services (WPSs) to facilitate service composition and chaining. All web services are registered into a service registry (module d) to make them discoverable and reusable by other researchers. The service registry is implemented as an OGC Web Catalogue Service (CSW) and the registration process contains two steps: parsing service metadata (module e) and insertion of these metadata into a back-end service database (module f). These components are the back-end settings of our GCI portal. In the front end, a web application server (module g) is deployed to communicate with the service database, pull out data and processing services as requested from a user and display them visually through the web map client (module h).

Figure 8. Service-oriented system architecture for the GCI portal. Items in blue show the protocols or standard interfaces for communications between different modules.

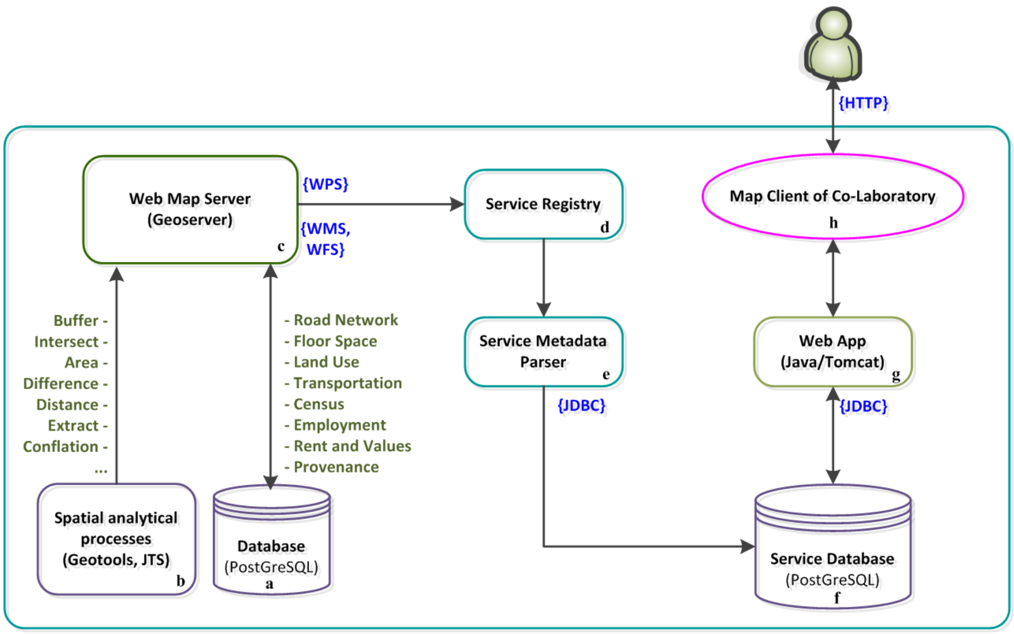
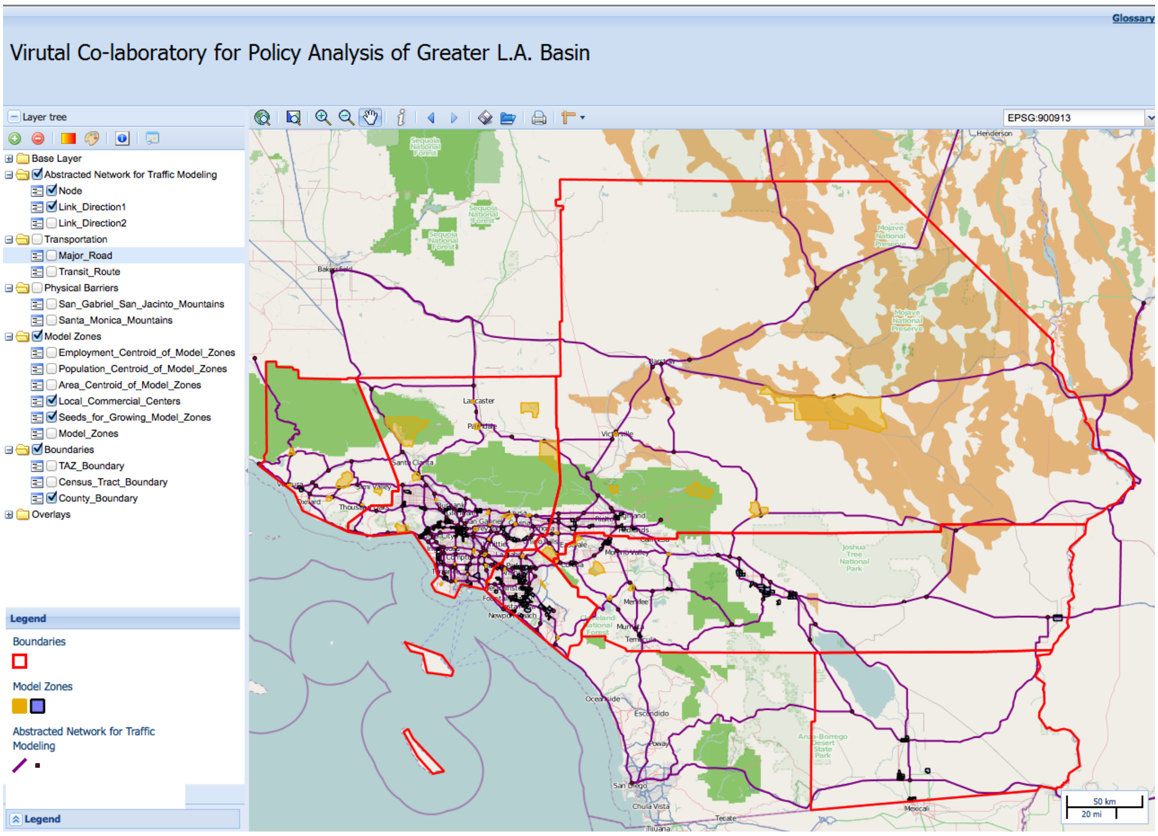


Figure 9 demonstrates the GUI (graphic user interface) of this urban GCI. The panel on the left-hand side lists available datasets organized in a hierarchical tree. Five categories of data are currently available: abstracted road networks, transportation, physical barriers, model zones and boundaries. By checking layers of interest, these data can be overlaid and displayed in the map panel. The map legend for each visible layer is displayed below the data layers. The base map of this user interface integrates high-resolution OpenStreetMap (http://www.openstreetmap.org) through its WMS interface. OpenStreetMap is a free world map that has been improved by volunteers all over the world. It contains information about basic geographic infrastructures and points of interest. In this interface, it is used as a reference for other data layers. This mapping interface provides Internet access to interactive maps and facilitates access to and integrated use of geospatial data. In addition, users with authorized access are able to download the original raw data with its provenance through this online interface or can invoke remote geoprocessing provided by the GCI.

Figure 9. Graphic user interface for the urban GCI [47].



6. Conclusions and Discussion

This paper reports on our findings based on our efforts to develop a GCI in support of urban policy analysis and decision-making through a service-oriented cyber-enabled online interface. We found that moving spatial analytical tools to cyberspace and providing adequate provenance information greatly facilitates the collaborative decision-making process. This proposed GCI is enhanced by three proposed techniques. The data conflation model ensures the fusion of data from multiple sources with improved spatial and attribute accuracies. The web processing framework facilitates tackling complex policy analysis tasks into a sequence of nested and chained geoprocessing services. The provenance feature enabled by this GCI design is able to trace the source and flow of data throughout the procedure of data processing. This feature substantially benefits decision-makers, especially geographically distributed decision-makers, in providing (1) a common understanding about the content of data and how the data can be used; (2) an assessment of datasets to aid in determining if they meet requirements (of data quality, accuracy, timeliness, *etc.*) of specific application needs; and

(3) replicability of datasets. We consider this work to be a pilot study of moving the urban economic simulation into an open web-based environment by resolving technical obstacles in information islands and dissymmetry of policy decisions through this open, interoperable and web-accessible platform. We expect a further adoption of GCI in terms of automated workflow composition and execution to contribute to effective spatial policy analysis and decision-making, as well as broaden the application coverage of GCI into urban economic simulations.

This project is still ongoing and our next step is to enable sophisticated system modeling through the RELU-TRAN model (Regional Economy Land Use—Transformation) [48] to establish a virtual collaborative laboratory and assess its performance in practice. This involves model validation and calibration in the back-end and a statistical analysis feature in the front-end of our GUI. In addition, as more data and services are being produced, we will develop a spatial search tool that utilizes advanced semantic search technology [49–56] to allow users to quickly identify the resources in need. Meanwhile, we will also develop an intuitive and user-friendly interface to manage the spatial analytical workflow and intermediate results generated through it. Once this virtual collaborative laboratory is fully established for urban studies in the LA region, we will extend our study area into other metropolitan regions that urgently need coordinated policy analysis, such as Beijing in China, to benefit broader communities.

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Conflict of Interest

The authors declare no conflict of interest.

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