

¹ MapSpace: POI-based Multi-Scale Global Land ² Use Modeling

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¹¹ — Abstract

¹² Accurate and up-to-date land use maps are important to the study of human-environment interactions, urban morphology, environmental justice, etc. Traditional land use mapping approaches involve several surveys and expert knowledge of the region to be mapped. While traditional approaches generate accurate and authoritative maps, it is expensive and takes a long time to develop a new version of map. Besides, such maps have region-specific spatial embedding, making them difficult to benchmark and compare against other land use maps. This work introduces a scalable POI-based land use modeling approach to generate global land use maps at multiple spatial scales and different semantic granularities. In addition, our land use maps adhere to a unified land use categories and can be compared for accuracy and precision.

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³¹ 1 Introduction

³² Accurate development of land use maps of a geographic region is critically important for the
³³ informed policy-making of different stake-holders, such as urban planning, environmental
³⁴ justice, and economic development. Points of Interest(POI) within a geographic region are
³⁵ suitable indicators of how humans use the space, and land use characteristics are often re-
³⁶ flected by the POIs within. The logical correspondence between POI features and land use
³⁷ types, coupled with the expanding coverage and timeliness of big POI data, offers research-
³⁸ ers a unique opportunity to model land use dynamics based on POI features (e.g., category)
³⁹ at varying spatial scales and semantic granularities. In this research, land use means the
⁴⁰ socioeconomic functions for which a land is used, not the physical nature or form of the
⁴¹ land surface. POIs' rich features can be projected in multiple dimensions, such as a spatial
⁴² dimension (i.e., geographic coordinates, polygons), a semantic dimension (e.g., functional
⁴³ use) and sometimes a temporal dimension (e.g., time of existence, opening hours). A com-
⁴⁴ bination of spatial distribution, semantic characteristics, and temporal dynamics of POIs

45 within an area of interest (AOI) reflects its unique land use characteristics. For example, an
 46 industrial factory usually has POIs like *warehouse, storage tank* whereas a recreational park
 47 would have amenities like *bench, playground*. Thus, the integration of spatial, semantic, and
 48 temporal aspects of POIs offers valuable insights into the land use dynamics at different
 49 spatial scales and semantic granularities. With the fast advancement of natural language
 50 processing research and growing geo-computing capabilities, the fusion and mining of spa-
 51 tial and semantic dimensions of crowd-sourced geographic information have gained lots of
 52 attention. Geo-referenced Wikipedia articles were used to identify spatial patterns of nat-
 53 ural hazards like wildfire across US [2]. POI data was integrated with word embeddings to
 54 classify urban land use at TAZ level [6] . [1] trained land use classifier for Europe based on
 55 POI-related features at grid cell level. The advantage of POI-based land use modeling is its
 56 general applicability to different geographic regions, and land use maps can be generated at
 57 different spatial scales and semantic granularities by adapting to the POI data coverage.

58 This short paper introduces a scalable POI-based approach for global land use modeling
 59 at multiple spatial scales and different semantic granularities. We will first discuss important
 60 factors for POI-based land use modeling, including data fusion, spatial scale, and semantic
 61 granularity. Then, we explore the most appropriate scale and semantic granularity for POI-
 62 based land use modeling at three different geographic regions around the world.

63 2 POI-based land use modeling



78 ■ **Figure 1** POI coverage of different POI data
 79 sources for Johannesburg
 80
 81

Different location-based platforms may par-
 64 tially overlap (or not) in their spatial data
 65 coverage. As seen in Figure 1, the spatial
 66 coverage of nine different online POI data
 67 sources is quite different from each other.
 68 Effectively fusing POI from these sources
 69 can significantly augment the coverage of an
 70 AOI. Besides, unlike remotely sensed images
 71 that have pixels covering the entire AOI,
 72 POIs are sample points scattered inside an
 73 AOI with rich information. There is no pre-
 74 set spatial resolution for the POI-based land
 75 use model. POI coverage could also vary
 76 from AOI to AOI. Therefore, the *spatial*
 77 *scale* and *semantic granularity* of POI-based
 78 land use modeling should be adaptive to spe-
 79 cific AOI. *Data fusion, spatial scale* and *se-
 80 mantic granularity* are three critical factors
 81 for POI-based global land use modeling.

83 2.1 Data fusion

84 Data heterogeneity across different data sources is common for non-authoritative crowd-
 85 sourced geographic data. Therefore, the effective fusion of heterogeneous POI data from
 86 diverse sources is critically important. Furthermore, the data fusion process could serve as
 87 a foundation for further incorporation of other data sources like social media data, ground
 88 images. In [3], we developed a Semantic Ontology Network (SONET) to deal with the
 89 heterogeneity of POI categorization across multiple data sources. The POI categories from

90 data sources were translated to *OSM tags* that serve as an intermediate semantic bridge. For
 91 example, *Restaurant* from Facebook, *food* from Google and *eatery* from Wikimapia are all
 92 mapped to OSM tags *amenity=restaurant;building=retail*. The OSM tags were effectively
 93 matched to data sources where POI categories vary not only in number but also in semantic
 94 granularity (e.g., general categories such as *restaurant*, and *hospital*, coexist with more
 95 specific categories such as *Italian Restaurant* and *Dental Hospital*). Furthermore, all the
 96 OSM tags are organized into a three-level land use category hierarchy. SONET is a graph
 97 database that contains 12,667 source linked categories from nine different data sources and
 98 is still growing.

99 **2.2 Spatial scale**

100 *Spatial scale* is a critical parameter for any spatial analysis. Concerning POI-based land use
 101 modeling, spatial scale refers to the spatial granularity at which we partition the space, and
 102 the resulting *spatial block* will be the smallest unit of which land use will be modeled. An AOI
 103 can be partitioned based on a simple grid and generate squared grid cells like image pixels,
 104 or it can be partitioned through Delaunay or Voronoi triangulation. These partitioning
 105 approaches emphasize the geometrical aspect of space. They do not pay enough attention
 106 to the geographical aspect of the space, i.e., how people interact with and use the space. One
 107 natural way to partition the space that can organically capture the way human activities
 108 interact with space is to partition the space based on the road networks. Road network is
 109 essential for people to carry out their daily activities and road network-based spatial blocks
 110 are organic spatial units for POI grouping and subsequent semantic clustering analysis. The
 111 hierarchy of segments in a road network naturally gives us the flexibility to partition space
 112 at different spatial granularities without losing spatial and semantic coherence.

113 **2.3 Semantic granularity**

114 *Semantic granularity* refers to the level of semantic specificity of land use category of a *spatial*
 115 *block*. For example, a spatial block can simply be labeled as *nonresidential*, or specifically
 116 *institutions/public services*, or more specifically *religious*. The semantic granularity of land
 117 use model is closely related to the spatial scale of the land use model. A small spatial block
 118 generated from lower-level roads (e.g., residential roads, service roads) can be assigned a
 119 fine-grained land use type, whereas spatial block generated from higher-level road network
 120 (e.g., tertiary roads) can only be characterized by coarser land use category.

121 **2.4 Multi-scale semantic clustering of POI tags**

122 With the data fusion process, POIs from different data sources are merged and translated
 123 into a collection of OSM tags. The data curation was achieved through the platform discuss
 124 in [5]. The spatial distribution and semantic composition of POIs within an AOI offer
 125 valuable insights into an AOI's land use. However, finding the appropriate spatial scale and
 126 semantic granularity for the land use model is critical. Figure 2 demonstrates the changes of
 127 land use maps as the spatial scale and semantic granularity change. We use topic modeling
 128 as a semantic clustering tool to explore the interactions between spatial scales and semantic
 129 granularity of POI-based land use modeling for three selected AOIs. Topic modeling is a
 130 collection of algorithms that uses probabilistic generative model to uncover the latent theme
 131 of a text corpus. In our experiment, an AOI is partitioned into spatial blocks with different
 132 levels of the road network. We model *POI tags* as words and group POI tags based on

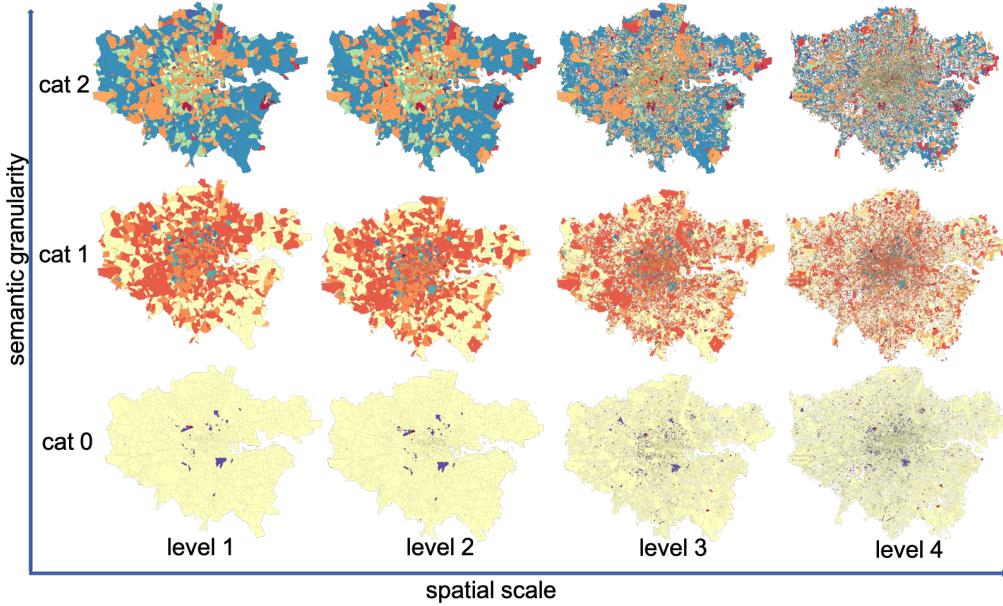


Figure 2 Land use maps change with spatial scale and semantic granularity

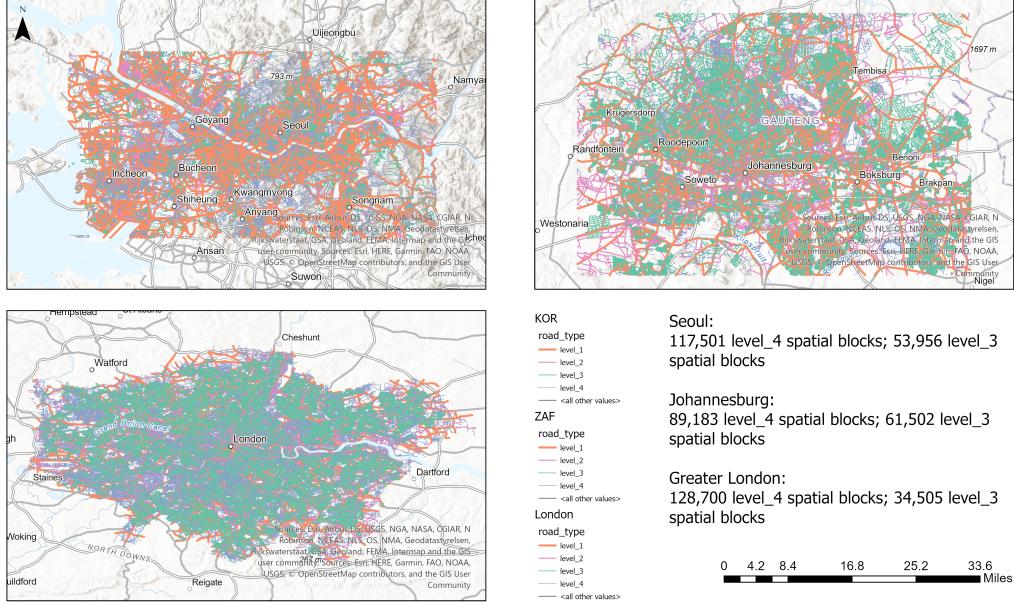
133 hierarchical spatial blocks generated from different levels of road networks. As a result, the
 134 POIs inside the same *level n* spatial block will form a *POI tag sentence*, the POIs inside
 135 *level n* spatial blocks that are inside the same *level n-1* spatial block will form a *POI tag*
 136 *document*. The hierarchical organization of POIs captures the spatial distribution patterns
 137 within a geographic region. The land use of a spatial block is modeled as the latent semantic
 138 topics over the *POI tag document* formed by POI tags.

139 **3 Experiment**

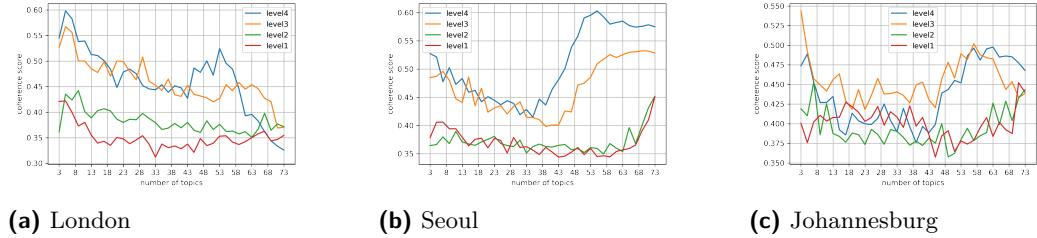
140 We test the efficacy of our approach on three AOIs from three different countries on three dif-
 141 ferent continents, including *Seoul (South Korea)*, *Johannesburg (South Africa)*, and *London*
 142 (*UK*) (as shown in Figure-3). The road network is divided into four levels: **level 1** roads
 143 include *tertiary* and higher than *tertiary* level roads, including *motorway*, *primary*, *trunk*,
 144 *secondary*, and *tertiary*; **level 2** roads include *unclassified* level roads in addition to *level*
 145 *1*; **level 3** roads include *residential* level roads in addition to *level 2*; and **level 4** roads
 146 include all the roads. For the POI data, nine different POI data sources were collected and
 147 semantically conflated for these AOIs.

148 **3.1 Interaction of spatial scale and semantic granularity**

149 For each of the three selected AOIs, we partitioned the space and generated spatial blocks
 150 at four different spatial granularities. By grouping POIs with spatial blocks of different
 151 granularities, we can create and evaluate the semantic clustering results at different spatial
 152 scales. In addition, we trained topic models with different pre-set number of latent topics at
 153 each spatial scale to test the effect of changing semantic granularity. By adjusting number
 154 of topics (3~75), the topic modeling can detect semantic clusters with varying granularities.
 155 Ideally, the best way to evaluate the topic models trained at different spatial scales and
 156 different semantic granularities is through human topic ranking, but they are expensive to



■ **Figure 3** Network hierarchy of three study regions



■ **Figure 4** Coherence scores of different topic models at different spatial scales

produce. Here, the result topic models are evaluated through semantic coherence measures [4], which are calculated based on pointwise mutual information between word pairs. Figure 4 shows the semantic coherence scores of all the trained topic models. For all three AOIs, the spatial blocks generated from lower-level road networks generated more semantically coherent topic models, indicating that lower-level road network such as residential roads and service roads can partition space in a more semantically coherent way. In other words, POI groups at a residential or lower-level spatial block reflect a more natural organization of human activities in space and how human use the space. For both Seoul and London, the *level 3* and *level 4* spatial block generates semantic clusters with similar coherency when the number of cluster is smaller than 35. When the number of semantic cluster is set to be greater than 40, *level 4* spatial blocks generates more coherent clusters. Both Seoul and London have two peak coherence scores (one at 3~8 clusters and another at 50~55 clusters) for *level 3* and *level 4* spatial blocks. For Johannesburg, *level 3* spatial block has better semantic coherence and it has peak semantic coherence around the similar number of clusters with Seoul and London. Table-1 shows the top three most coherent topics for each of the AOI for topic models trained with *level 3* spatial block and 10 pre-set topic.

Three AOIs have different land use themes. For Seoul, the top three are retail/restaurant, mixed residential and commercial, and tourism/entertainment. For London, its residential, retail, transportation; For Johannesburg, its retail, industrial and leisure/recreation.

AOI	Top 3 themes
Seoul	<ol style="list-style-type: none"> 1. payment;pharmacy;route;cuisine;cafe;retail;smoking;market_route_ref;coins;amenity_fast_food 2. building;apartments;amenity;commercial;leisure;platform;highway_bus_stop;school;park 3. motel;sauna;hotel;capacity;level;bar;사우나;leisure_fitness_centre;cinema;농협
London	<ol style="list-style-type: none"> 1. building;residential;house;amenity;leisure;parking;amenity_post_box;platform;highway_bus_stop;bench 2. shop;retail;restaurant;convenience;cafe;open_data;level;drive_through;hairdresser;church 3. route_bicycle;network_lcn;colour;cycle_network_gb;layer;housenumber;london_cycle;co_uk
Johannesburg	<ol style="list-style-type: none"> 1. shop;parking;restaurant;surface;supermarket;cuisine;amenity_fast_food;convenience;amenity;pharmacy 2. railway;industrial;gauge;route;rail;electrified;service;bus;platform;contact_line_frequency 3. leisure;park;pitch;sport;leisure_swimming_pool;tennis;playground;soccer;leisure_sports_centre;golf_course

■ **Table 1** Topic model results with highest semantic coherence scores.

176 4 Conclusion

177 Accurate and precise land use maps are essential to modeling finer-resolution population
 178 distribution, measuring the growth of urban sprawl, and studying the societal and cultural
 179 phenomenon. This concept paper introduced a globally applicable multi-scale land-use mod-
 180 eling technique based on the spatial and semantic dimension of POI data. Also, we demon-
 181 strated the selection of the most appropriate spatial scale and semantic granularity for land
 182 use modeling on three diverse and geographically apart regions of the world. In the future,
 183 we plan to introduce temporality, socio-economic, and other factors to generate vibrant land
 184 use maps at planet-scale and develop universal benchmarks to validate land use maps.

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