Overview of Location Analytics and Decision Support

James B. Pick
School of Business
University of Redlands
james_pick@redlands.edu

WORKSHOP ON LOCATION ANALYTICS AND LOCATION OF THINGS: CONNECTEDNESS AND COLLABORATION
Pre-ICIS Workshop
San Francisco
Wed. Dec. 13, 2018

University of Redlands School of Business

Topics covered

- What are location analytics, decision support, and spatial decision support systems (SDSS)
- Trends leading up to location analytics, and modernized SDSS
- Two examples of location analytics and decision support
- A framework of location analytics and decision support research
- What are the gaps and prospects for research in the areas of decision making with location analytics, and modernized SDSS?
- Conclusion
- Questions and discussion

What are location analytics, decision support, and spatial decision support systems (SDSS)

- *Location Analytics* is the contemporary concept of using specialized spatial analysis techniques to understand spatial distributional patterns and relationships to geographically referenced phenomena.
- *Geographic Information System* (GIS) is a system that analyzes or models spatially-referenced data and comes up with solutions involving location.
- *Spatial Decision Support System* (SDSS) "combine spatial and non-spatial data, the analysis and visualization functions of GIS, and decision models to estimate the characteristics of problem solutions"(modified from Keenan and Jankowski, 2019)

UNIVERSITY OF Redlands School of Business

Trends leading up to location analytics, and modernized SDSS

- There had been continuous improvement in capabilities of information technology to support spatial decision support systems.
- GIS software has over time substantially expanded and improved the tools for spatial analysis and geoprocessing
  - Today software packages such as ArcGIS Pro have many hundreds of analytics features, compared to only dozens when the SDSS field got started in the 1970s.
  - GIS software and DSS modeling software were originally difficult to integrate toghether but this has become gradually easier to do with time.

Effect of the Internet and mobile devices on SDSS

- The possibilities of public participation SDSS were greatly expanded by the increasing power of the Internet. This trend has expanded the SDSS usge. Today public participation SDSS is available in GeoHubs.
- Since modern mobile phones have GPS, cell phone triangulation, and other spatial location sensing, the opportunity for SDSS on mobile devices has grown and spread globally.
- Internet-based location analysis is sometimes referred to as location-based services (LBS). LBS opened up new types of SDSS, such as decision-making on precision agriculture, i.e. enabling the farmer to decide on precise, meter-square, application of fertilizers.

Influence of Spatial Data on SDSS

- Spatially-referenced data have become vastly more available since 1980s.
- Governments have expanded extent of spatial referenced data.
- Private sector gathers it intensively.
  - Private sector even tracks daily location of millions of people, unbeknownst to them (article in NY Times, 12-10-18).
- Social media is spatially-referenced and some providers (Twitter) make the data available publicly
- Many sharing-economy business models are location based – Uber, Airbnb
- Open and crowd-sourced data are location-based e.g. OpenStreetMap, which provides a digital map of the world, using a crowdsourcing model similar to Wikipedia's
- **The availability of vastly more data has spurred the expansion of use of SDSS**

Your Apps Know Where You Were Last Night, and They're Not Keeping It Secret

Dozens of companies use smartphone locations to help advertisers and even hedge funds. They say it's anonymous, but the data shows how personal it is.

By JENNIFER VALENTINO-DeVRIES, NATASHA SINGER, MICHAEL H. KELLER and AARON KROLIK DEC. 10, 2018

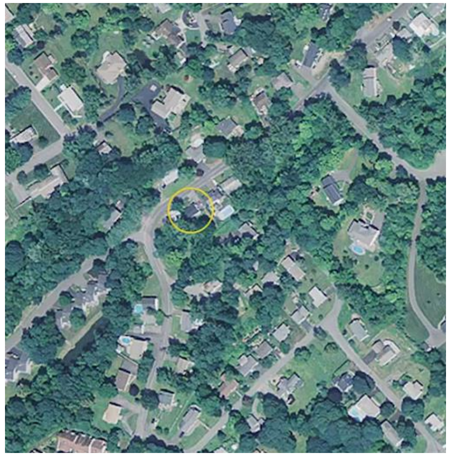
The millions of dots on the map trace highways, side streets and bike trails — each one following the path of an anonymous cellphone user.

One path tracks someone from a home outside Newark to a nearby Planned Parenthood, remaining there for more than an hour. Another represents a person who travels with the mayor of New York during the day and returns to Long Island at night.

Yet another leaves a house in upstate New York at 7 a.m. and travels to a middle school 14 miles away, staying until late afternoon each school day. Only one person makes that trip: Lisa Magrin, a 46-year-old math teacher. Her smartphone goes with her.

An app on the device gathered her location information, which was

Lisa Magrin's Daily Start from her home



Lisa Magrin's Daily Destination – school

(Source: DeVries et al, 12-10-2018)

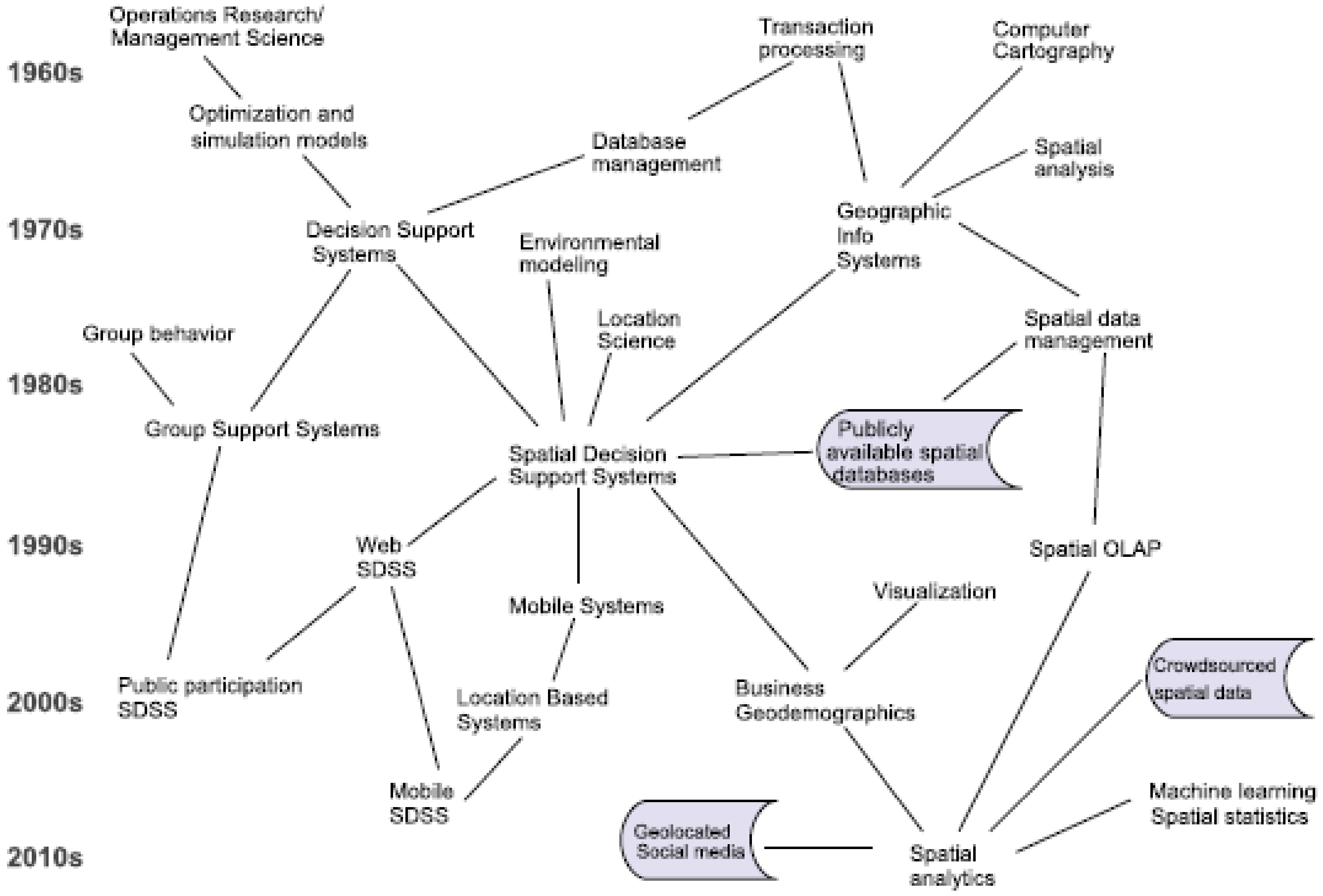
Big Data, Cloud Computing, and Visualization are Spurs to recent development of SDSS

- Big Data represents the amassing of huge data sets, often including spatial referencing.
- Cloud computing has provided locations with the storage and capacity to process huge spatial databases with powerful GIS software.
- These trends have sparked a broader range of Location Analytics and SDSS models as well as practical applications.

Spatial Statistics, Location Analytics, and Machine Learning

- Spatial Statistics are statistical techniques that take into account spatial proximities and include geographically weighted regression, spatial autocorrelation, spatial Markov structure, Bayesian estimation of spatial data over time, etc.
- Location Analytics is a form of Analytics (popular in MIS field). Analytics goes beyond traditional spatial statistics to provide analytical tools to address big data, i.e. data with hundreds of thousands or millions of records. Traditional statistics and spatial statistical cannot be applied to full-size big data due to effect size.
- Modern location analytics techniques including data mining, visualization, data slicing and dicing, optimization, simulation, sentiment analysis, text analysis, and monte carlo simulation, are applied to spatial datasets.
- Machine learning can be applied to large spatial data-sets to develop better prediction.

The genealogy of the SDSS field



(Source: Keenan and Jankowwski, 2019)

Two examples of location analytics and decision support

- Examples of location analytics combined with decision support are becoming more common in the IS and decision science literature. In the special issue of *Decision Support Systems* (vol. 99, July 2017) on this topic, two studies are discussed that illustrate two approaches to location analytics and decision support.
- Facility location using GIS and location analytics, enriched with demographic data, for a traveling entertainment troupe in Bavaria (J. North and F.L. Miller, DSS, vol. 99, 2017).
- Location intelligence applied to carsharing decision support in European metropolitan areas (C. Willing et al., DSS, vol. 99, 2017)

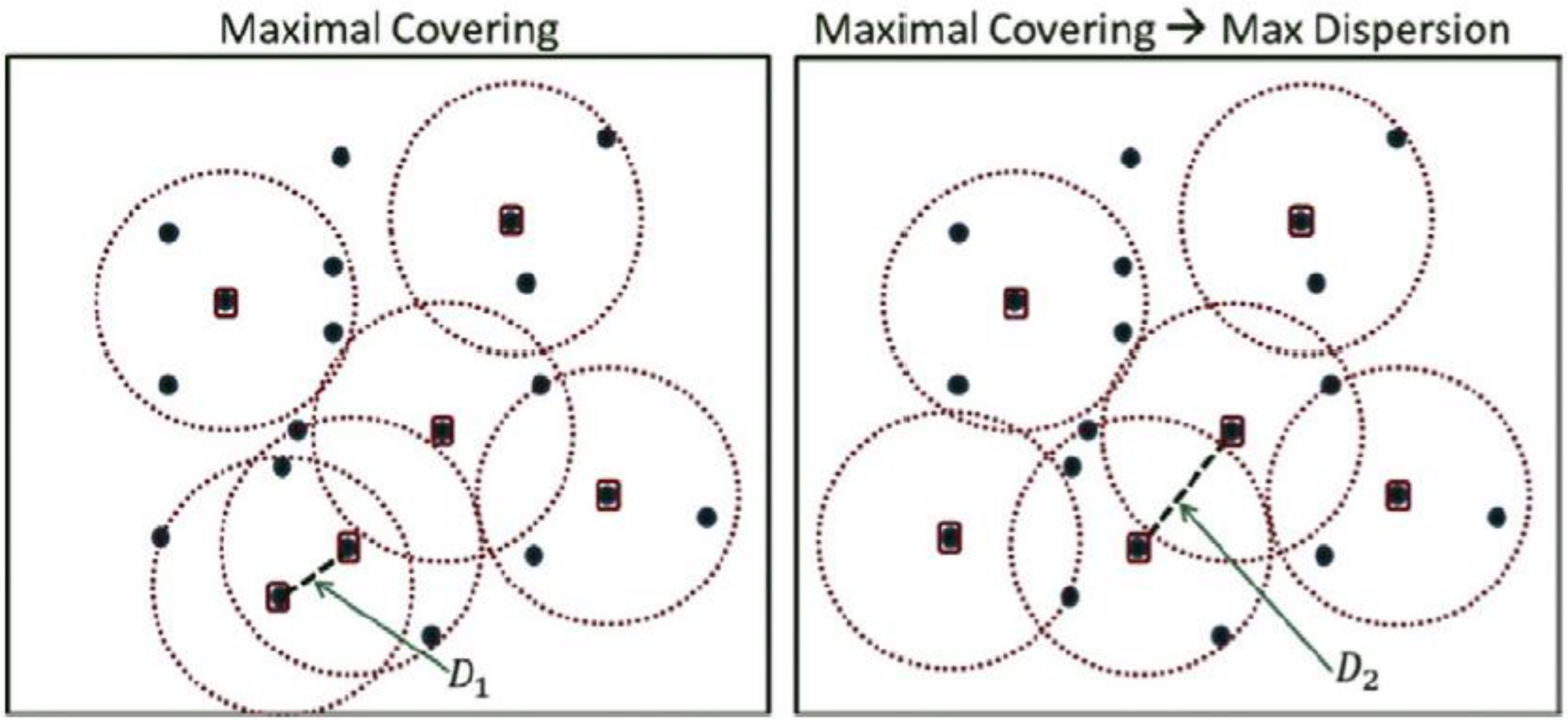
- These two examples are intended, in this workshop, to illustrate the potential modeling power and practical application of location analytics combined with decision support.

Facility location method to select good show locations for traveling entertainment troupe in Bavaria, Germany

- The troupe, headquartered at a Munich theater, seeks to expand its market by offering shows at optimally-located sites across Bavaria.
- A multi-criteria facility location method is used to determined the expanded locations of the troupe across Bavaria.
- Customer information is based on demographic and consumer-spending data is available from Esri Business Analyst for the 95 districts in Bavaria.
  - These data are used, in the SDSS, to weight consumer demand level and lifestyle population at the postal-code geography.
- Optimization of locations is performed that maximizes amount of customers within a given travel distance from a show, while maintaining dispersion of the selected facilities.

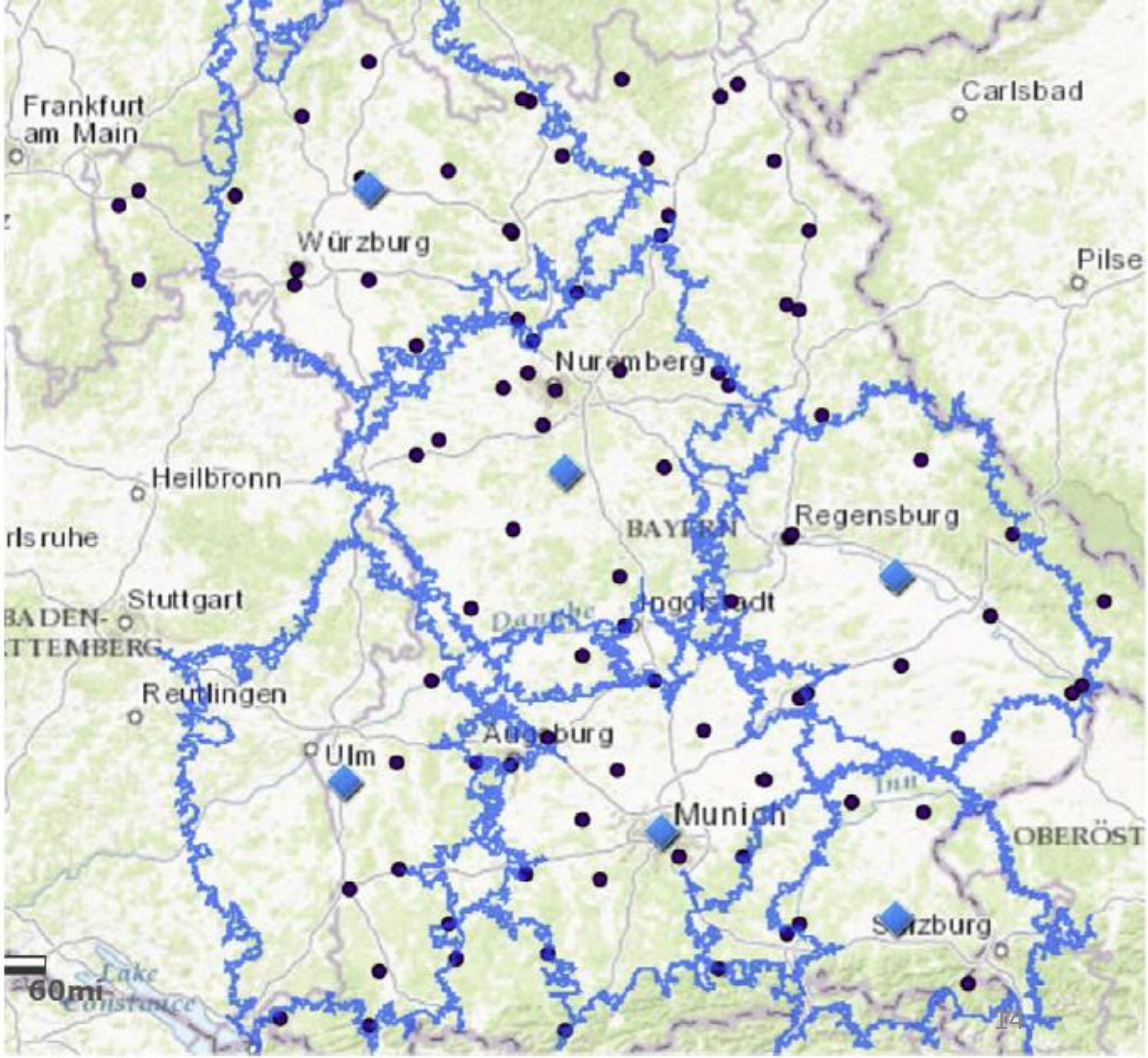
(Source: North and Miller, 2017)

Multiple Optimality of Locations in Maximal Covering of Customer Demand for Bavarian Troupe Sites



(Source: North and Miller, 2017)

Selected locations and coverage of the 95 districts of Bavaria using the model assumption (P3′,λ=1).



(Source: North and Miller, 2017)

Summary of study on German entertainment troupe

- This study's methodology represents an integration of an operations research-based approach to facility location, in order to optimize the decision on locations), utilizing the large stores of locational-referenced data available in Esri's Business Analyst.
- The operations research approach is a multi-criteria facility location model for the p-dispersed maximal covering facility location problem (PDMCLP).
- The connection between location analytics and decision support is through data enrichment of a class in the locational optimization for decision-making.

(Source: North and Miller, 2017)

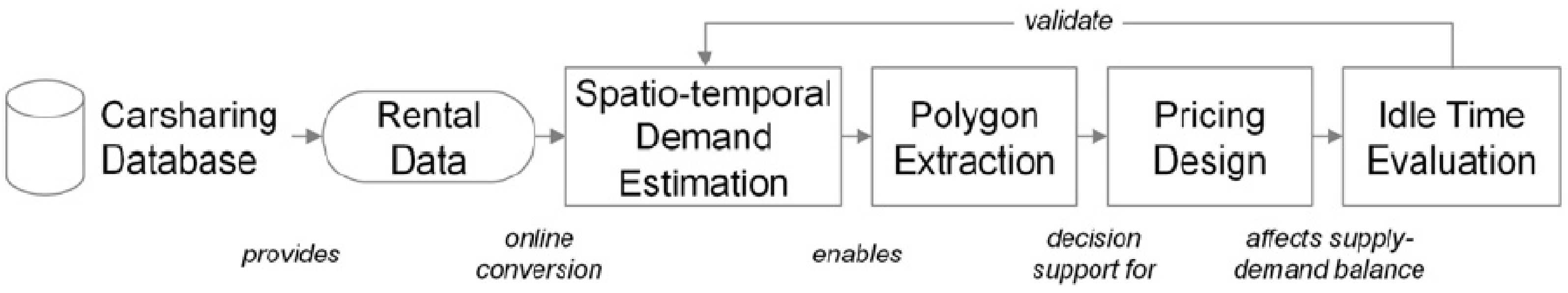
Location intelligence applied to carsharing decision support in European metropolitan areas

- This spatial decision system (Willing et al., 2017) helps providers of free-floating carsharing services understand and correct imbalances between vehicle-driver supply and customer demand, and was tested using data from an important carsharing provider in Amsterdam, utilizing locations of points of interest (POI) as well.
- Descriptive findings for Amsterdam are used to predict carsharing demand in Berlin. The model can be prescriptive for defining new business high-demand areas and exclude low demand areas in a new city.
- There is strong integration in this example between location analytics and decision support.

(Source: Willing et al., 2017)

University of Redlands School of Business

Location Analytics and decision support model for carsharing in City of Amsterdam



- Areas in the city of high or low demand reflect a higher or lower densities of trips.
- Carsharing users can feely chose a location to end a trip, but start of trip depends on supply level.
- The model assumes carsharing companies benefit by having more vehicles in the areas of high demand, which improves fleet utilization and in turn higher profits
- The model, through linkage with a GIS, estimates spatial heatmaps of demand based on historical density data.
- High and low demand polygons are used as pricing areas to encourage customers to end rides in high-demand areas and discourage riders ending in low-demand areas. Consequently, following this pricing approach, idle times will be reduced.

Points of Interest (POI) are added and merged using kernel density estimation

- Use of grid centers of 100m x 100m areas for all of Amsterdam results in 6,664 points.
- Each point is assigned to POIs and rental destinations within a defined distance.
- The process is repeated for times-of-day and for day-of-week subsets.
    - Using all the subsets, and applying regression, it is estimated how changes in patterns of POIs relates to changes in carsharing.
    - More processing is done using gradient boosting, to select POI categories with highest explanatory power, and using generalized linear model (GLM) that is discussed in the paper.
- These ensemble modeling steps lead to demand levels, that can be used to determine pricing zones.
- The resultant pricing is influenced by POI categories, the effects of which vary by day of week and time of day.

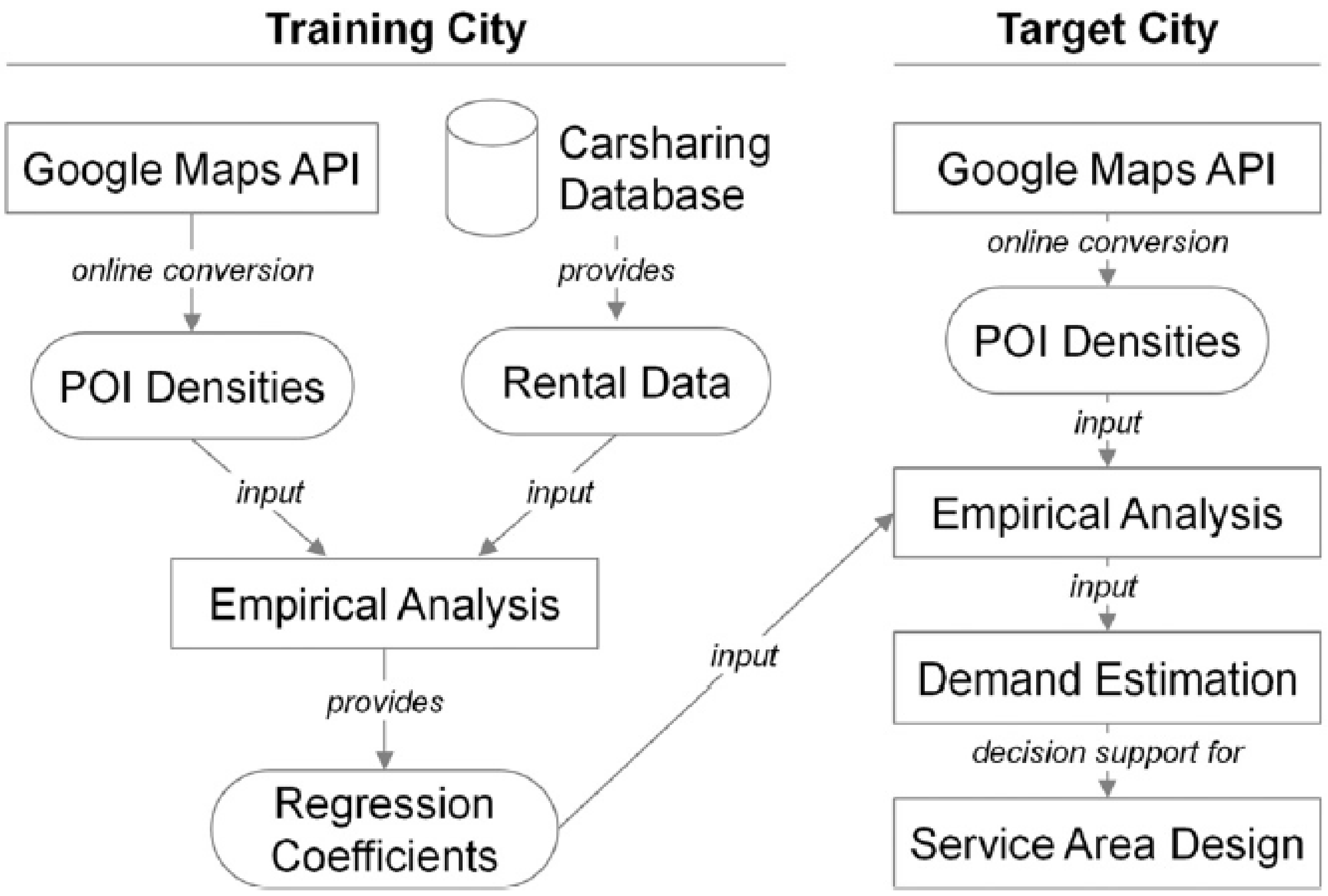
After incorporating POIs, Resultant demand quantiles (M-F) are used to determine the shape of pricing zones.

(a) All trips (b) 4:00 – 8:00 (c) 20:00 – 0:00

In summary, this model for Amsterdam of carsharing integrates the location analytics of ensemble modeling with decision making on pricing to correct imbalances, reducing vehicle idle time.

University of Redlands School of Business

Further step: Carsharing for training city, e.g Amsterdam applied to targe city, e.g. Berlin: Predictive spatial location analytics



(Source: Willing et al., 2017)

Classification of Levels of Strength and Depth of Location Analytics

1. Spatial data manipulation. This is an elementary use of locational analysis that simply produces the raw geographic information; sometimes referred to as "dots on a map," because the dots as raw data are not further organized or elaborated on to become information or knowledge. Spatial data manipulation does not have a location analytics component.

2. Spatial data analysis. This is more descriptive than Level 1, and often exploratory. Techniques of spatial analysis are used, including overlays, buffering, spatial autocorrelation, hotspot analysis, proximity polygons, 3-D, rastering, location quotients, Huff modeling, and spatial econometrics. Spatial data analysis considers the geospatial and geometric relationships of the mapping elements.

(Source: Pick et al., 2017, based on O'Sullivan and Unwin, 2014)

University of Redlands School of Business

Classifica-tion of Levels of Strength and Depth of Location Analytics

3. Spatial statistical analysis. At this level, data are used in estimating a statistical model or solvable optimization model that recognizes spatial properties.

4. Spatial modeling. This level uses heuristics, simulations, and combined methods in an integrated model that are expressed spatially.
The goal is to answer questions such as can the model express geographic flows of persons and material objects, optimize the location of business offices and facilities, or simulate real world complex locational environments and situations .

Spatial modeling goes beyond the solvable spatial statistical models in step 3 and consists of deterministic or stochastic modeling and simulation that includes spatial elements.

(Source: Pick et al., 2017, based on O'Sullivan and Unwin, 2014)

University of Redlands School of Business

Background to a framework of location analytics and decision support research

- A majority of previous work on location analytics and decision support also incorporated non-location related components such as the underlying(non-locational) research problems, non-locational data utilized and/or generated, and non-locational analytics methodology.

- The dimensions of integration between location analytics and decision support research that we propose in the framework are: (a) conceptual integration,(b) algorithmic/software integration, and (c) integration as it appears to the user.

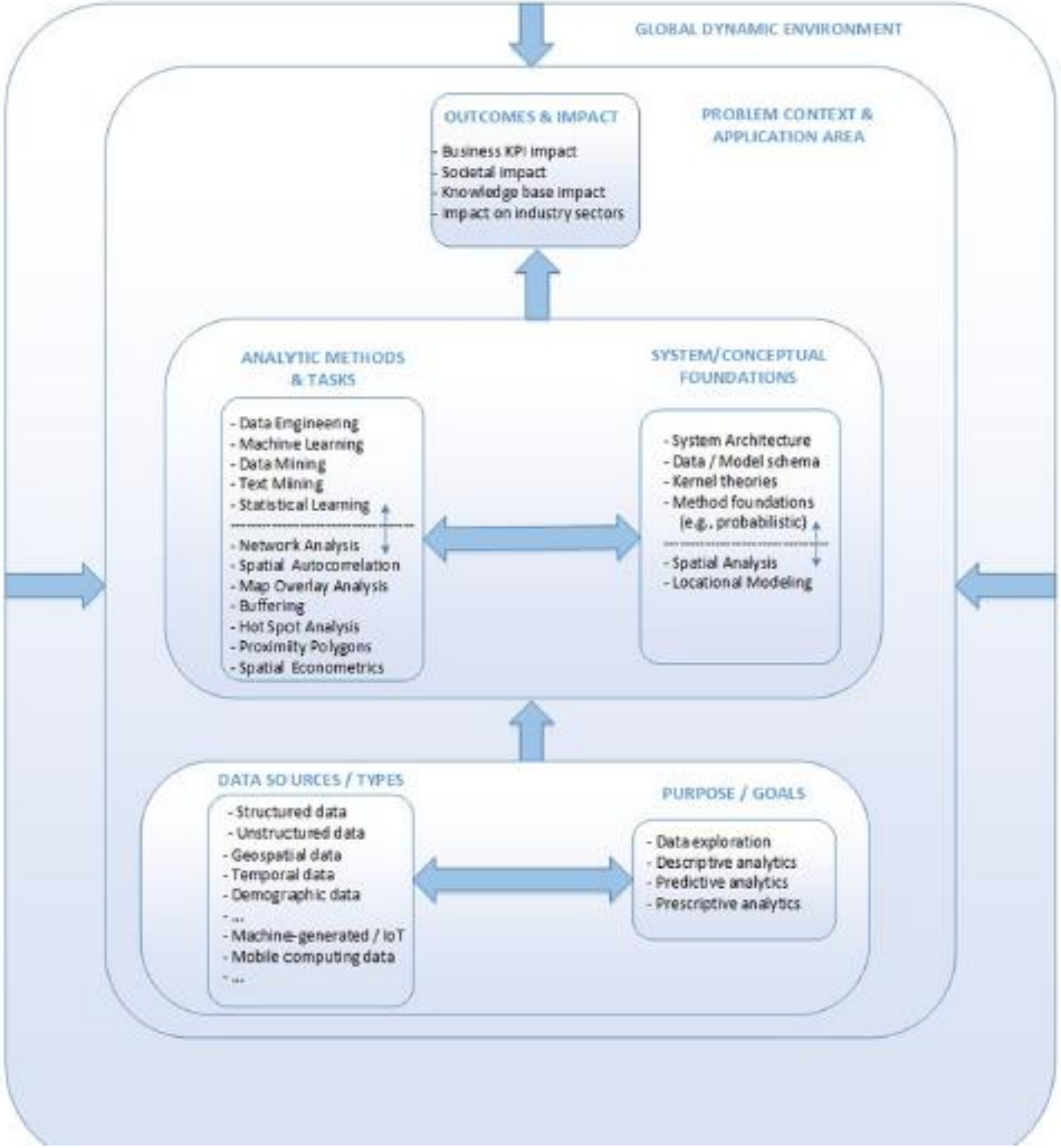
Framework for location analytics and decision support

This overall framework depicts key elements in a typical locational analytics and decision support research project.

This framework is an abstraction based on the observations from the extant body of research in this area published in the journal *Decision Support Systems* (Pick et al., 2017)

The goal of the framework is to provide a generic way of linking new research in this area to prior or existing work.

Framework of location analytics and decision support research



(Source: Pick et al., 2017)

Gaps Identified in Location Analytics and Decision Support Research

(1) One gap that has future potential is research on LA/NLA/DS which expands the variety of geographic and spatial techniques . For instance, researchers could consider decision support models that utilize Getis-Ord statistics, kriging, geographically weighted regression, spatial econometrics, local indicators of spatial association (LISA) techniques, Huff modeling, among others which are in common use in geographic information science.

(2) Another area of future potential is to continue the trend noted of stronger integration of LA, NLA, and DS. There are synergies in doing this that can potentially lead to more powerful, efficient models and tools.

(Source: Pick et al, 2017)

Gaps Identified in Location Analytics and Decision Support Research

(3) Often LA/NLA/DS research investigation has been stronger conceptually on the NLA side, with excellent explanations of optimization, statistical, and heuristic theories and framework, but limited in spatial theory. Advancements in this area might derive from enhancing and adapting existing geographic and spatial theory and combining it with the mainstream DSS theories. Another approach would be to combine several existing spatial theories that apply to decision making.

(4) Research opportunities exist in the emerging research area of big data and in particular its unprecedented ability to process the rapidly expanding spatial information flows from social media, sensors, drones, satellites, and RFID-based locations to analyze how this flood of data interacts with socio-economic information at varied levels of analysis leading to distilled information kernels for predictive decision making

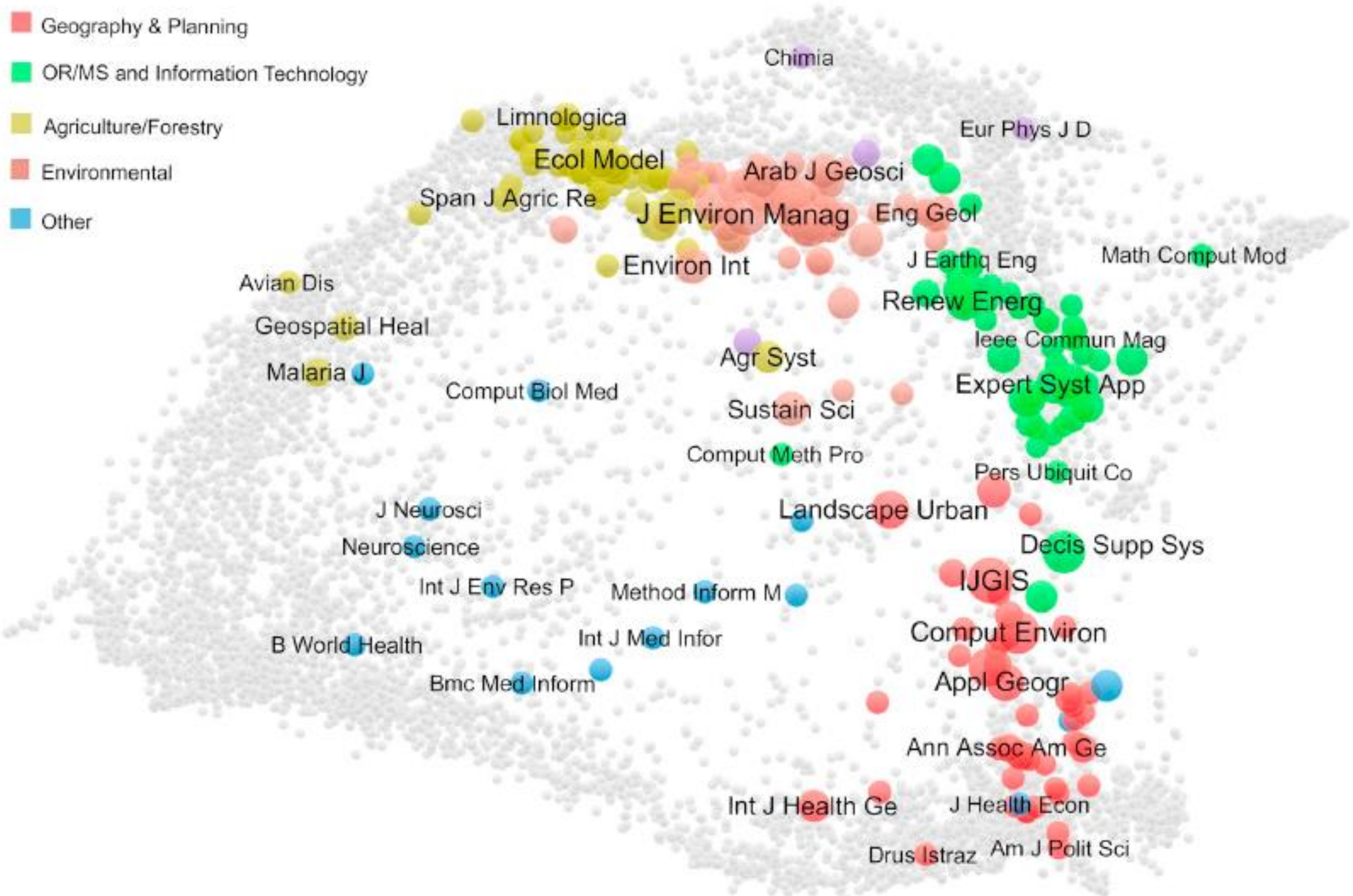
(Source: Pick et al, 2017)

What are the prospects for journal research in the areas of decision making with location analytics, and modernized SDSS?

- A detailed study of the SDSS literature (Keenan and Jankowsky, 2019), using the Web of Science, has shown some major divergence in published SDSS research from the central MIS core of literature, although the core group of over 30 IS and OR/MS journals such as *Decision Support Systems and Expert Systems Applications* are still present It has identified many journal outlets in areas that are interdisciplinary and have major concern with locations, the earth and geography, including the following:
- Geography and Planning
- Environmental
- Agriculture and Forestry
- Healthcare

University of Redlands School of Business

SDSS publications in Web of Science, 2015



(Source: Keenan and Jankowski, 2019)

Conclusion

- Location Analytics, GIS, and Spatial Decision Support Systems have evolved considerable and today are being studied in a modern context.
- There are underlying trends in technology which point to these technologies becoming pervasive.
- Two examples are given of the integration of location analytics and decision support.
- A generalized framework is given for LA and DS.
- Some gaps are discussed in the present state of research that offer research opportunities
- Publications in this area have included OR and MIS, but have extend considerably into other interdisciplinary journals as well.

University of Redlands School of Business

References

Keenan, Peter Bernard, and Jankowski, Piotr. 2019. Spatial decision support systems: three decades on. *Decision Support Systems* 116:74-76.

North J., and Miller, F.L. 2017. Facility location using GIS enriched demographic and lifestyle data for a traveling entertainment troupe in Bavaria, Germany. *Decision Support Systems* 99:30-36.

O'Sullivan, D., and Unwin, D. 2014. *Geographic Information Analysis. Hoboken, NJ: John Wiley and Sons.*

Pick, James B., Turetken, Ozgur, Deokar, Amit V., and Sarkar, Avijit. 2017. Location analytics and decision support: reflections on recent advancements, a research framework and the path ahead. *Decision Support Systems* 99:1-8.

Willing, C., Klemmer, K., Brandt, T., and Neumann, D. 2017. Moving in time and space – location intelligence for carsharing decision support. *Decision Support Systems* 99:75-85.

Questions and Discussion ???

James_Pick@redlands.edu