AUTOMATED CONFLATION FRAMEWORK FOR INTEGRATING TRANSPORTATION BIG DATASETS

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The undersigned, appointed by the dean of the Graduate School, have examined the thesis entitled

AUTOMATED CONFLATION FRAMEWORK FOR INTEGRATING TRANSPORTATION BIG DATASETS

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A candidate for the degree of Master of Science,

And hereby certify that, in their opinion, it is worthy of acceptance.

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ABSTRACT

The constant merging of the data, commonly known as Conflation, from various sources, has been a vital part for any phase of development, be it planning, governing the existing system or to study the effects of any intervention in the system. Conflation allows enriching the existing data by integrating information through numerous sources available out there. This process becomes unusually critical because of the complexities these diverse data bring along such as, distinct accuracies with which data has been collected, projections, diverse nomenclature adaption, etc., and hence demands special attention. Although conflation has always been a topic of interest among researchers, this area has witnessed a significant enthusiasm recently due to current advancements in the data collection methods. Even though with this escalation in interest, the developed methods didn't justify the expansions field of data collections has made. Contemporary conflation algorithms still lack an efficient automated technique; most of the existing system demands some sort of human involvement for the analysis to achieve higher accuracy. Through this work, an effort has been made to establish a fully automated process to conflate the road segments of Missouri state from two big data sources. Taking the traditional conflation a step further, this study has also focused on enriching the road segments with traffic information like delay, volume, route safety, etc., by conflating with available traffic data and crash data. The accuracy of the conflation rate achieved through this algorithm was 80-95% for the different data sources. The final conflated layer gives detailed information about road networks coupled with traffic parameters like delay, travel time, route safety, travel time reliability, etc.

CHAPTER 1 INTRODUCTION

The process of enhancing one dataset with the additional information available in different forms and formats from various sources has been here since the term ‘data collection’ has been coined. This process of augmenting information of a source by supplementing data is known as Conflation. The practice of conflation is not restricted to any particular field, from subjective fields of psychology, biology to the fields as diverse as transportation engineering, the use of tools from time to time to enhance the current data sets is prevalent. In this study, we are using the concept of conflation for the integration of transportation big data sets from various sources to get a final layer of the road network which will have supplemented information from all the conflated layers.

The initial practice of conflation was usually achieved by overlaying, intersecting and cross-referencing of map layers manually to get a final map with all the statistics and projections from the different map layers. The problem of data inconsistencies both in the spatial and attribute domains presents obstacles in using data for analysis, overlays, and mapping. The need for integration of these diverse data has become principally important with the current advancements in the technology and the ease in the data collection methods. With the increase in the efficiency of data collection, the size of collected data has increased exponentially and that’s why the term big data has become a part of various field’s argot as well. While trading with data it is usual to encounter different geospatial sources that bring anomalies and heterogeneity along as the nomenclature and accuracy adopted vary with sources of data. It becomes difficult to identify the same features from distinct data sources due to different ways the data is represented in a different way. These irregularities can be overcome manually if the size of data is manageable; nevertheless, this becomes infeasible as soon as data begins to inflate and hence demands some sort of sophistication in dealings.

Due to all these progressions, the technology has made and dynamic changes in the data availability and propensity, there is a dire need to find a tool that can automate the process of the conflation with a higher accuracy that can handle the integration of datasets in such a big scale.

1.1 Conflation- An overview

Initially, the primary objective of conflation was to eliminate any sort of spatial inconsistency from the various vector maps to achieve a desirable accuracy. The primary objective of removing such altitudinal discrepancies was to allow easier transfer of attributes from one map to another [1]. From there the utilization of conflation has become quite diverse, from removing discrepancies to adding missing details, it has found uses in various aspects of data integration. Geographic Information Systems (GIS) is one of the important fields where conflation plays a vital role mainly due to the size of such files and it is hard to get all the data from a single source. To do any GIS analysis, there is always a factor of heterogeneity that needs to be addressed as the GIS data assemblage is pretty tedious and still expensive to be afforded by a single agency. By default, such kind of data brings along a large number of inconsistencies among information accumulated from various sources. In the field of transportation engineering, GIS data plays an important role, from traffic designs, Intelligent Transportation System (ITS) to transportation planning, every aspect requires some sort of GIS data analysis. For the different GIS layers, the traditional methods mostly comprise of using Rubbersheet or Align features which take care of the anomaly inaccuracies, misalignment, etc., among the data; however, their application is limited, time-consuming and not so satisfactory, especially, when dealing with transportation big datasets.

Conflation is not only limited to dealing with the same data type, but there are also certain regions where it requires to find a relation between information belonging to different data type altogether. For example, the crash data usually comes in an excel or a CSV file whereas the road data on which these crashes occur come in either GIS or excel/CSV format, for a better visualization of the fusion of these two data sets, a GIS conflation would do more justification as compared to a simple excel file merging. The visual representation of data like a heat map, the color symbolization of road network based on crash type can be achieved only if the relationship between these different data types/sources can be established. Because of such atypical requirements, another aspect of conflation which has started gathering attention is data fusion; the interest in data fusion has become quite substantial in the recent time mostly due to the need of working with different data type from various sources. If we see the field of big data, these data comprise of information collected from many sources and have a completely different data type, even a simple representation of this data needs coordination and correlation among these data sources and type.

A typical example of the conflation of road networks from two data sets has been shown in figure 1.

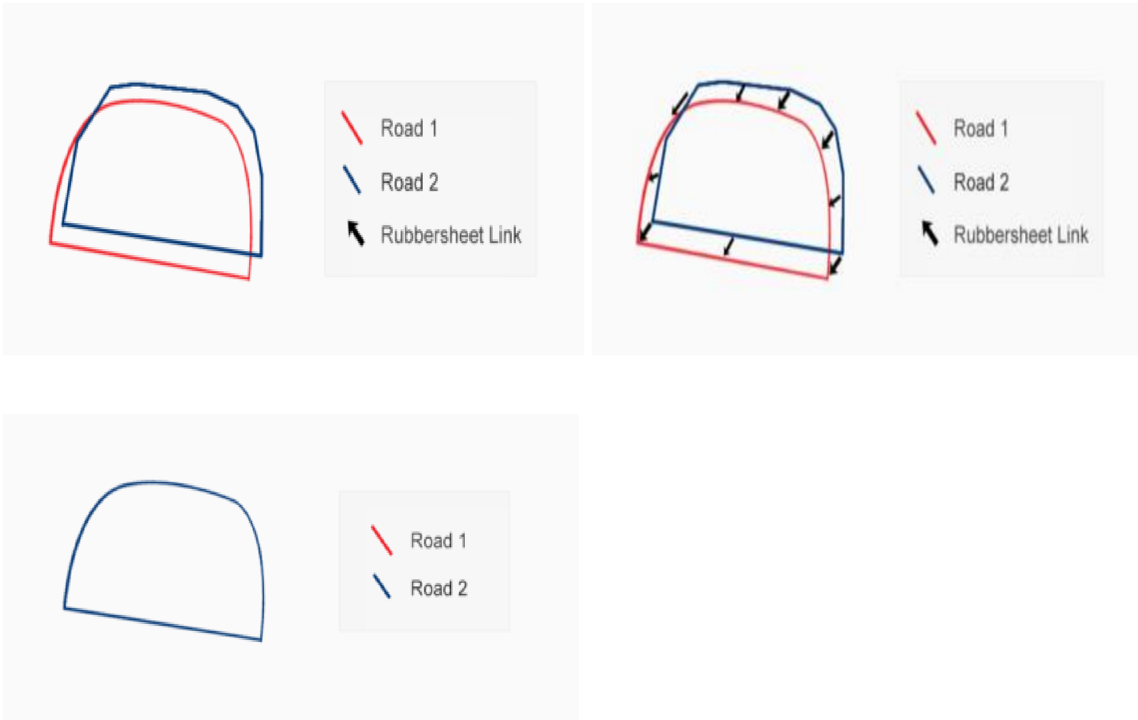


Figure 1: Conflation- An Overview[35]

This study focuses on creating a layer of the road network for the Missouri state which is going to give information spatial information like location, length, etc., as well as traffic parameters like the direction of traffic, delay, congestion, as well as safety parameters like a number of crashes, route safety, etc. The study has employed various facets of conflation for the amalgamation of these transportation big datasets for various analyses. Since this research work is dealing with big data and requires a lot of computations, this study focused on creating an automatic algorithm rather than a manual or semi-automated process for the integration of these datasets. The successful deployment of an automated algorithm, evidently, is a novel approach as most of the available methods entail some sort of human intervention. On a small-scale data size, manual editing approaches probably attest to be less cumbersome, nonetheless, as the map scales and attribute increases, such type of practices become very tedious and practically impossible to achieve.

For this study, data available from free sources as well as State DOT's data were used for the analysis. There were primarily five types of data used to achieve the objective set for this study and they were viz. MO-DOT Linear Referencing System (LRS) data for road networks (LRS), INRIX road data, MO-DOT detector data which gives information like traffic volume on road networks, Missouri road crash data of three years and Saint Louis transit data which gives real-time location of buses on road network for a week which would help in the computation of traffic variables like delay, congestion on the road networks for the Saint Louis County.

1.2 Problem Statement

In the field of transportation engineering, it is quite usual to encounter data of a different kind and then trying to establish a relation among them to derive some interpretation for the overall transportation system. The transportation data collection is still a big scale and an expensive investment, and this is one of the key reasons that it is hard to find data from a single source. This is simply due to the monetary as well as the human effort which goes in the collection as well as maintenance of such large data sets. Even among a county, data collection report varies with the agency to agency and it is hard to form a single organization dealing with all aspects of one data type. Crash reports for different types of the accident on roads is a classic case of nomenclature anomalies, hence the application of conflation is far and wide in transportation engineering. Due to this diverse data type, the conflation of various data sets is usually achieved by manual methods using tools like excel; since the transportation data numbers are increasing exponentially, manual methods found to be expensive, inefficient and sometimes even counterproductive. The proposed methodology is going to deploy an automated conflation algorithm which not only overcomes the diverse data problem but also eradicates the requirement of manual conflation by employing data fusion and features alignment through the programming language as well as the GIS tools for analysis as data chosen for this study comprises of GIS as well as CSV data. The ready to use tools available in the market were also used for the comparison of the proposed method and it was found that the automated algorithm proved to be more accurate and computationally efficient as well. Thus, the proposed tool is capable of dealing data sets on a big scale as well as overcomes the problem of heterogeneity with satisfactory accuracy.

1.3 Objectives of the study

The objectives of this study can be summarized in the following points:

- *The conflation of diverse data sets*: In this study, the tools for the conflation of multiple layers is to be developed using the theory of overlaying, feature matching as well as data fusion. The layers matching in this study include:

    - LRS and INRIX: An algorithm is to be developed to conflate big data sets of road shapefiles collected from two sources viz. INRIX and MO-DOT. This tool would aim to develop a final layer with enhanced information from both datasets by surmounting spatial discrepancies, accuracies, and differences in nomenclature adoption.

    - INRIX and Crash data: A tool is proposed here to fuse the data from two different types of information background using a common linear reference used on the road network. This procedure would lead to the assignment of crashes from crash reports to respective road networks.

    - INRIX and Transit data: The third methodology planned to be designed here would use the concept of data fusion to align the information from different resources viz. road shapefiles and real-time location of transit system on road networks, to analyze traffic variables like delay congestion, travel time, etc., on the county-wide road networks.

- *Automation:* This study aiming to provide a tool that can handle big data sets with feasible time consumption as well as provides easier scalability to diversified data type by automating the whole process of conflation. Another aspect of automation that's been targeted through this work is achieving a cost-effective tool with satisfactory accuracy which would discourage the tedious human intervention altogether.

CHAPTER 2 LITERATURE REVIEW

Before getting started with the proposed methodology, a literature review has been done on the development of Conflation methods using the various theories over the years. The literature review has helped to understand the growth of this research area and find the gaps where this process of conflation can be tweaked to justify the improvements technology has made.

The process of assimilation, as well as the orientation of different forms of data sets, can be defined using the term. The conflation process can be divided into the following subtasks: [3]

1. Feature matching: Find a set of conjugate point pairs, termed control point pairs, in two datasets.
2. Match checking: Detect inaccurate control point pairs from the set of control point pairs for quality control.
3. Alignment: Use the accurate control points to align the rest of the geospatial objects (such as points or lines) in both datasets by using the triangulation and rubber-sheeting techniques.
4. Data Fusion: The integration of data from numerous sources to get a final data set which will have combined information for a better understanding of the information.

Conflation found its first application around the mid-1930s but the research work in this field was really sparse; it was only in the late 1980s that this area has gained popularity among researchers mainly due to the advancements in technology which has made various kinds of data easily available. With the increase in data collection and growth of the internet, there was an increased interest in working with data to get a fair chance to prove the researcher's own interpretations. The development of this tool over the years can be better understood in the following paragraphs.

The conflation of road segments has been gathering its due interest since the 1980s [1]. A lot of effort has been put afterward [2][3][4]. The research work on conflation started with very basic intention of improving the existing maps with information available in different forms and different sources. The methods adopted during 1980 were mainly focused on making this process as much as automated as possible. With the use of Rubber sheets in [1] [4] computer recognizes matches between different maps using mathematical algorithms and graphical positions to detect similarity [4]. During initial times the methodologies were mainly inspired by statistical methods like proximity of locations and geometry [5]. Rather than considering conflation as a single method, it has been considered this as a multistep iterative process namely, positional re-alignment of component maps, identification of matching features and positional and attribute deconfliction of positively identified feature matches [5]. In [6] this work has talked about transferring attributes from one layer to another or adding missing features. Previously geospatial databases (GDBs) played an important role in accumulating information from heterogeneous sources [7]. The work like [8],[9],[10] presented studies to justify the need for merging information from the database with different forms and density, with varied precision values. In [11], Spatial Data Infrastructure has been adopted to make a framework that would allow the data interchange between different systems. Works like [12],[13],[14] talked about data fusion, a traditional method, for the integration of two layers and getting a third layer with supplemented information from both the layers. These works were particularly famous in the field of remote sensing and GIS [15]. According to [16], even though the conflation term finds its roots in the 1980s, it didn't see much of the development until the mid-2000s. The work of the 1980s mainly witnessed the work of gathering images and maps, development of computational methods based on graphics and geometry. The conflation method has been primarily dependent on the feature matching be it a line to line (road to road), polygon to the line (buildings to the road), point to the line (position to the road), etc. The aforementioned features are known as geo-objects and determination of relations between these features is known as matching [17]. Earlier studies have based their work on the above principal like matching of geo-objects to achieve a conflation [2], [4], [5], [6]. With the advancement in computational methods, the conflation methods became much more detailed and rather than adapting generalized feature matching like proximity and feature it became subtler with the intention of higher accuracy. The methods like distance, angle, buffer growing, etc. had taken a matching process of data from various sources to a higher level [17]. There have been extensive studies on matching features like roads or buildings commonly known as polygon conflation [18], [19], [20] to make the traditional maps more informative. The work in [5], [7], [21], [22], [23], [24] had underlined the significance of over-lapping important geometric structures like intersections, roundabouts, etc., these works had used this important location like geometric infrastructures on-road segments for conflation and coined methods based on this principle. After the successful implementation of this theory, it became quite popular among researchers and had been a part of the coming conflation methods, meanwhile, features like Linear and

Topographical matching had seen a boost among researchers too. With this achievement of higher accuracy, now the focus of the researchers shifted from accuracy to automating this process, especially for handling data on a large scale. Works like [26], [27], [28] had focused their attention on automating this process as well as achieving higher accuracy. In [29] the cynosure of this work had been automating the procedure in a semi-automated way. This work had utilized cluster matching algorithms to find a strong connection between nodes, edges, and segments; the interactive procedure, on the other hand, allows a user to rectify the mismatched features which were missed by an automated mechanism. This approach was a breakthrough in automating the conflation process; however, user intervention was still a complex way to achieve

reliable results. The work of others like [30], [31] used their works for the specific type of road patterns rather than focusing on being generic and hence the scalability of these methods decreased significantly for other types of road segments. Based on the literature review for this work, it is evident that there is still a good scope for a robust automated conflation algorithm which can help in achieving higher accuracy, with no user interference, whatsoever, and still has the scalability to be adapted for all the types of road segments. There was little to no work seem to be done to inculcate the traffic aspect of road segments in the map as this was mostly done manually and due to the size and complexities of this data, it was usually preferred to confine it for an area of interest itself. This project has focused on taking conflation methods from just improving spatial data quality to providing more road-specific information like traffic, safety, etc.

This paper has been arranged as follows: Section 3 will be talking about the methodologies adopted for this procedure. From data preparation to conflation time, the information regarding each step of this algorithm has been discussed here. Section 4 talks about the results and discussion regarding the outcomes from the conflation. And at last, Section 5 talks about the key take away from this work and the future work which can be done to make this procedure more efficient in the field of conflation.

CHAPTER 3 PROPOSED METHODOLOGY

The methodology developed for automating conflation of the LRS and INRIX datasets and extended to other datasets includes four key steps: Data pre-processing which prepares the two geographic data layers in the best condition for further analysis. Next, ESRIs ArcGIS tools such as “Detect Feature Change” are used to detect spatial and geometric changes in both datasets. For segments where no change is observed, a one – to – one mapping is carried out. If there was a spatial change, features are matched based on proximity, topology, and pattern and similarity analysis. Finally, specific feature attributes from the source layer are transferred to the matching target features to generate an output crosswalk table. The overall conflation rate achieved is approximately 95%. The conflated road segments from LRS and INRIX are then further improved with some real-time traffic data by conflating time position of transit data, detectors in the roads, and crash data collected for the Missouri state. Transit data consist of the real-time position of buses with the timestamp and trip details congregated for a selected county for two consecutive weeks and were conflated with INRIX road segments. Using the combined information of INRIX’s average travel time on road segments and travel time gathered from transit data, the traffic variable delay was calculated; the output of this traffic data viz, delay employed for interpreting the traffic flow of the route. This understanding of flow was achieved by conflating another set of traffic layer collected from the detectors placed in various highways. The detector data brought the important variable traffic count to the existing map. This spatially joined data with vehicle count and delay helped to comprehend reasons for the delay such as, whether it is controlled or uncontrolled one. The amalgamation of crash data with INRIX, on the other hand, helped to give an idea about the safety issues of the state roads, overall. Crash data is the crash report on the various roads on Missouri noted with respect to mile marker with all the details regarding accident and surroundings and this mile marker was used as cross-reference while achieving the conflation. This experiment with the conflation of data from various GIS sources as well as real traffic data not only gave a map with enhanced spatial information but was also successful in giving a richer picture of traffic-related queries like travel time, delay and safety of the roads.

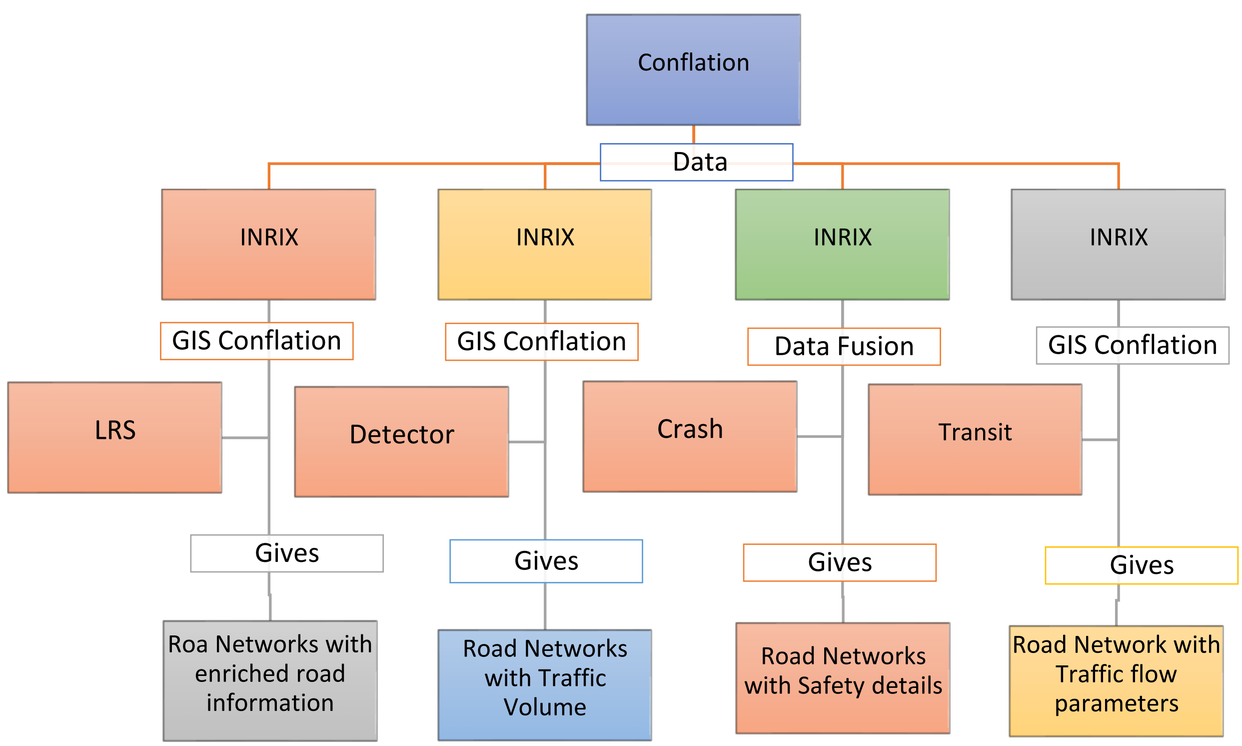


Figure 2: Adopted Process for conflation

3.1 INRIX and LRS Conflation

3.1.1 Traditional GIS conflation toolsets

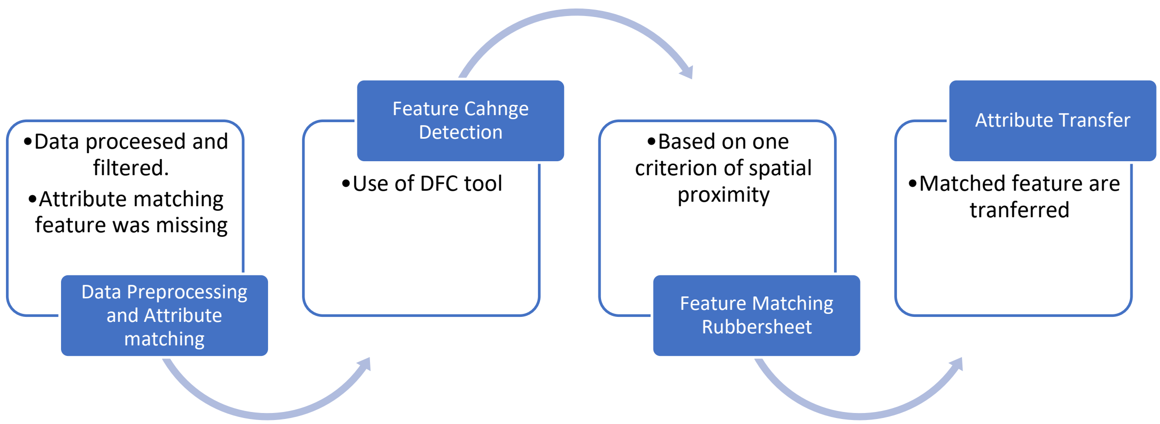


Figure 4: Traditional Conflation tool flow chart

Data Pre-Processing and Attribute Matching.

This step prepares the data for the best condition possible for further analysis. The two geographic data layers are collected from two separate vendors. As a result, the potential for geometric and attribute data inconsistencies is high. The pre-processing stage includes validating data geometry and topology, selecting relevant attribute features (e.g. road names, segment ids, counties, etc.) for processing and using consistent map projections to ensure that the two data layers are projected on the same geographic coordinate system.

Next, attributes in both datasets describing the same features are matched.

Attribute matching feature wasn't found in the available conflation toolsets and due to this, there is a high rate of mis conflation i.e., one feature matching to a different segment in different data sets. Through this proposed method, the matching criterion has been fixed to overcome the issue of false conflation and make the process more viable and efficient.

Accuracy: Because the conflation process relies on spatial proximity, a road segment A, in one layer could be conflated to two road segments, B and C, in another layer although the bearing (direction of traffic in this context) of either B or C might be opposite to the bearing of A.

For the GIS conflation tool since there is no tool to match the features, the traditional conflation toolsets use the proximity measure as only matching criterion which leads to conflation error. That is, the possibility of matching one INRIX layer to the LRS segment would completely be dependent on the distance between these two features.

Detect Feature Changes

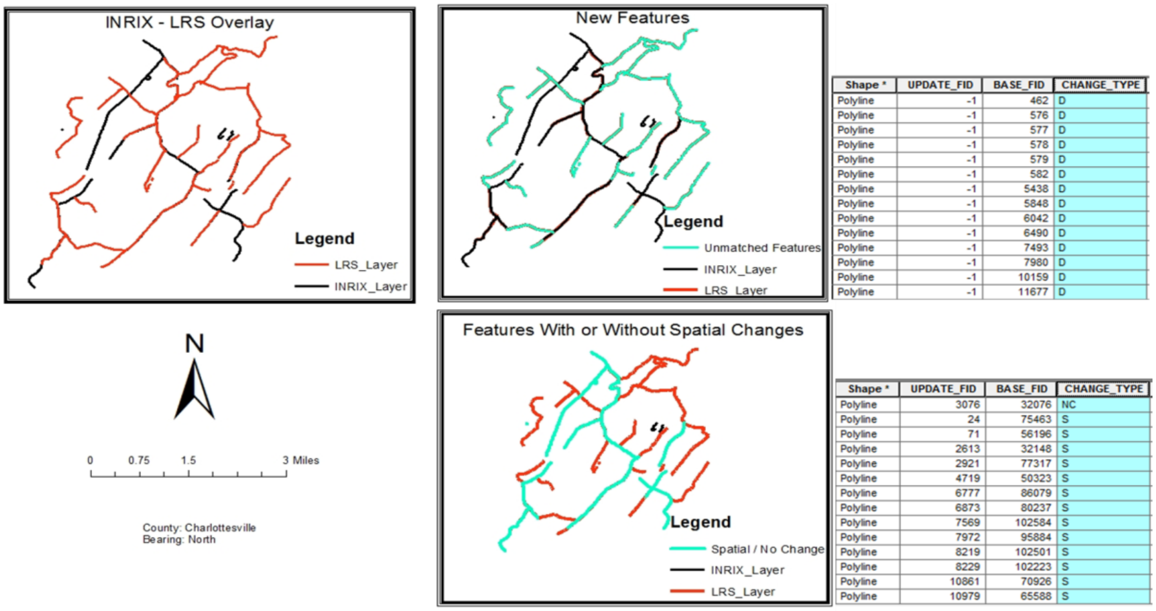
Feature change detection is the first step in the implementation of the conflation process. Knowing where and what the changes are between the two datasets helps you assess how significant they are and whether or not you need to proceed with attribute transfer.

To detect feature changes in both datasets, the DFC tool in ESRIs ArcGIS was used. This tool identifies spatial feature differences and outputs the type of change detected for each feature. Ideally, there are four (4) possible changes that could occur:

- Spatial Change (topological difference)
- Attribute Change
- No Change (1:1 match without any spatial or attribute changes)
- New feature (unmatched feature).

Figure 5 shows the results of using the DFC tool to detect feature changes in a selected region on both datasets. For features where a spatial change was detected, the following workflows will be used to unify and consequently conflated into the base data which is the

LRS in this case.



Shape *	UPDATE_FID	BASE_FID	CHANGE_TYPE
Polyline	-1	462	D
Polyline	-1	576	D
Polyline	-1	577	D
Polyline	-1	578	D
Polyline	-1	579	D
Polyline	-1	582	D
Polyline	-1	5438	D
Polyline	-1	5848	D
Polyline	-1	6042	D
Polyline	-1	6490	D
Polyline	-1	7493	D
Polyline	-1	7980	D
Polyline	-1	10159	D
Polyline	-1	11677	D

Shape *	UPDATE_FID	BASE_FID	CHANGE_TYPE
Polyline	3076	32076	NC
Polyline	24	75463	S
Polyline	71	56196	S
Polyline	2613	32148	S
Polyline	2921	77317	S
Polyline	4719	50323	S
Polyline	6777	86079	S
Polyline	6873	80237	S
Polyline	7569	102584	S
Polyline	7972	95884	S
Polyline	8219	102501	S
Polyline	8229	102223	S
Polyline	10861	70926	S
Polyline	10979	65588	S

Figure 5: Results of using the DFC tool

Feature Matching

The goal of feature matching is to map features in the source datasets (INRIX layer) which experienced a spatial change to its corresponding target features (LRS layer).

For the traditional conflation tool - For the sake of comparison, ESRI’s ArcGIS feature matching tools were used in this project. These tools match distorted features based on proximity, topology pattern and similarity analysis, and other optional attributes. An output of this step is a table storing match information.

The specific tool used in the current study is the “Generate Rubbersheet Tool” shown in figure 6. This tool generates links between matched features or points where the source and target locations are identical. Figure 7 shows the results of using the rubbersheet tool to match INRIX and LRS segments on Interstate 29 East (I-29E). A total of 352 (representing 91%) unique INRIX segments were accurately matched to their corresponding LRS segments. The gaps in the rubbersheet results frame (green layer) shown in figure 7 (part b) represent regions where road segments were not mapped. The conflation rate does fluctuate depending on the type, geometry, and length of the road segment. The overall conflation rate for all road segments will be evaluated in the results section.

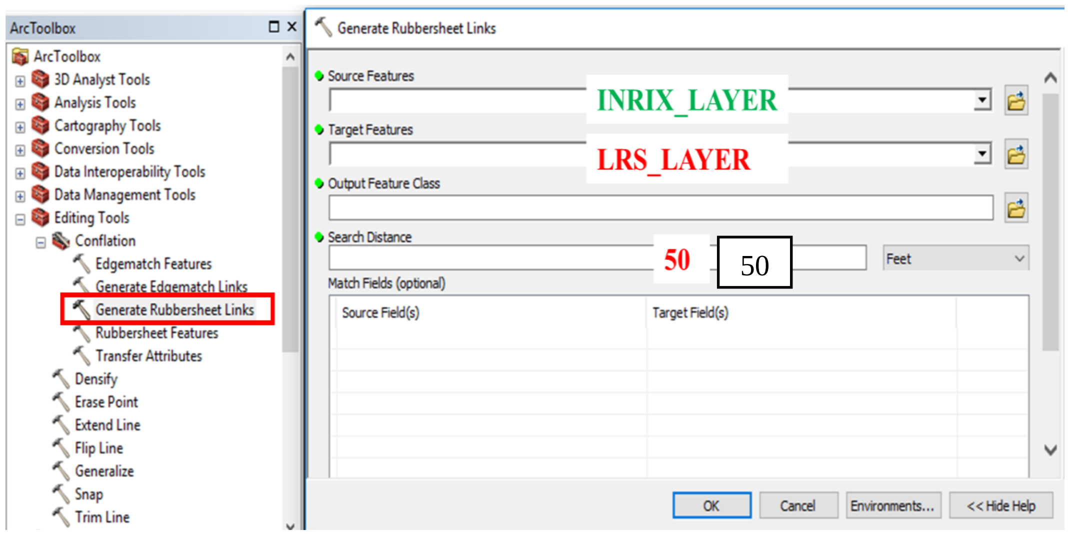


Figure 6: ArcGIS Rubbersheet Tool for Feature Matching

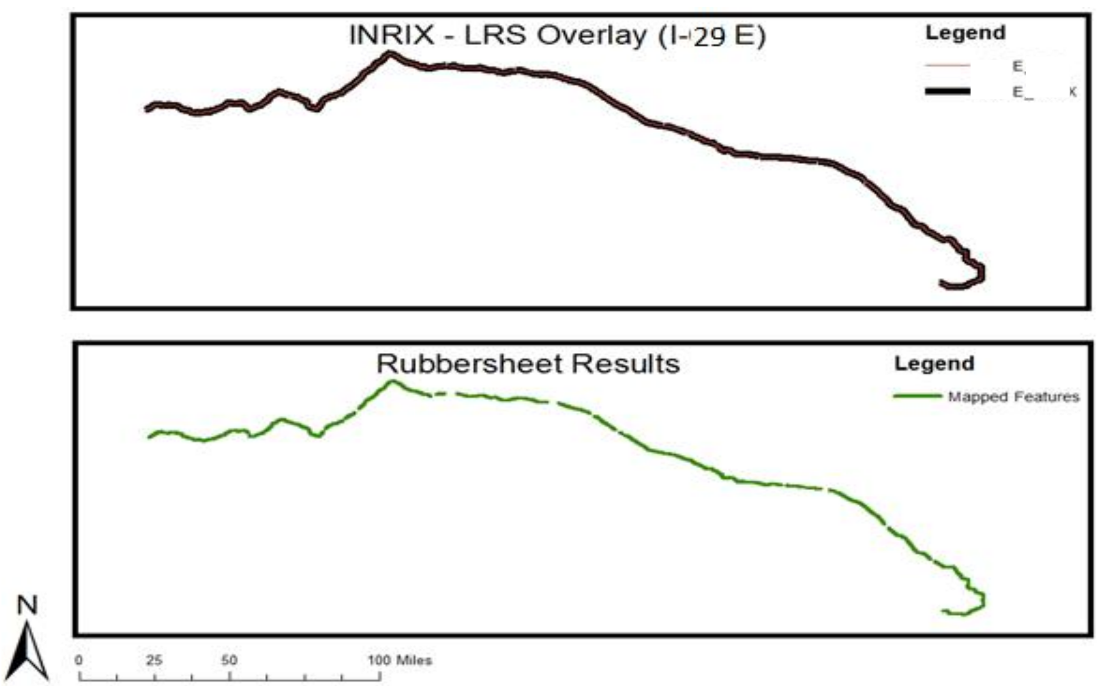


Figure 7: Feature Matching Results for a Selected Road (I-29).

Transfer Attributes

Finally, once features between the two geographic data layers have been matched, specific feature attributes from the source layer are transferred to the matching target features. Table 1 shows an example transfer attribute output table.

Table 1: Transfer Attribute Output Table

INRIX_ID	LRS_ID	INRIX_NAME	LRS_NAME
119-16706	189028	12TH ST	12TH ST
119-19151	346042	18TH ST	18TH ST
119+14152	198748	31ST ST	WYANDOTTE ST
119-19041	346313	4TH ST	4TH ST
119N16741	186825	6TH ST	CHARLOTTE ST
119N16741	186686	6TH ST	6TH ST
119+13415	296790	AIRPORT RD	AIRPORT RD
119P13415	297903	AIRPORT RD	170

The traditional tool not only lacks the sophistication tools required to deal with diverse data but also computational infeasible while dealing with big data sets like the road networks used here. From table 1 it is evident that there was mis conflation, for example, airport road is conflated to 170 and 31st Street is conflated to WYANDOTTE ST. Since the criterion of matching was only based on the proximity, this tool fails to encompass the data inconsistency and assortment.

The approach designed for this study tries to overcome the main drawbacks of existing tools and modify the conflation process to encompass such anomalies. The process is discussed in detail in the following section.

3.1.2 Proposed Methodology

The proposed methodology uses the same four steps of conflation as its basic criterion, the flow of this methodology is shown in figure 8. The following subsections would discuss each step-in detail for the adopted approach here.

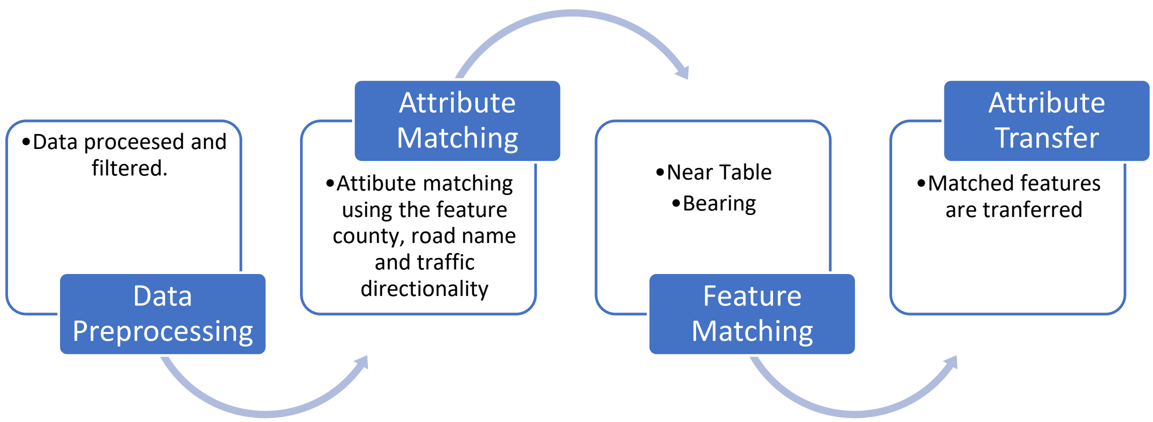


Figure 8: Proposed Methodology flow chart

To make sure the process is fully automated python language is used for coding using various libraries. Most of the functions were defined as per the requirement for this algorithm, and some famous libraries like **pandas**, **arcpy**, **numpy**, **os** to achieve the following steps using python language. The steps of basic conflation are tweaked to address these irregularities in the datasets.

Data Processing and Attribute Matching

The data preprocessing filtering is pretty much the same as explained for traditional GIS toolsets.

Attribute Matching: For the attribute matching, the matching feature has been designed to achieve an accurate conflation rate. For this matching criterion, three main attributes were considered and matched in the intended approach: County, Road Name and Road Directionality. Attribute matching improves the accuracy and processing speed of the conflation process, significantly. The process of looking at each feature in the given dataset, not only makes this process computational infeasible but also encourages the false conflation and skews the conflation rate. This issue becomes pronounced especially while dealing with big datasets like MO road networks, for example, used here. To avert this, the proposed algorithm considers the filter of road attributes apart from spatial proximity to boost accuracy. This, basically, means the road names, as well as directionality in both layers, must be matched to ensure that conflation is carried out only between similar road segments with the same directionality.

Conflating both layers at the state level is very time-consuming due to the number of road segments involved and computer memory limitations. County and road level information is used to reduce the computational load per each iteration, resulting in a much faster system. There are, however, county and road naming inconsistencies between the two layers. For instance, where LRS will use “Beech Ave.” to describe the name of a road, INRIX will use “Beech Avenue”. The current study used text analytics and, in some cases, used a dictionary to match such inconsistencies in attribute naming conventions between the two layers. For the text algorithm, Sequencematcher is used from **difflib** library in python. The matching is based on the probability of similarity between matching words. Table 2 shows an example results of the attribute matching step.

Table 2: Road name attribute matching results

INRIX Road Names	LRS Road Names
CHIPMAN RD	CHIPMAN ROAD
12TH ST	E 12TH ST
8th ST	E 8TH ST
EMANUEL CLEAVER II BLVD	S EMANUEL CLEAVER II BLVD
COLBERN RD	E COLBERN RD
SCHERER PKWY	S SCHERER PKWY
D	MO-D
FOREST PARK PKWY	E FOREST PARK PKWY

Apart from road names, there are some inconsistencies incurred in road directionality as well. Due to data collection or feeding inaccuracies road names and directionality assignments in both layers are inconsistent. There are several instances where one vendor assigns a "North" direction to a segment and the other vendor assigns "East" to a corresponding road. Based on the study of such anomalies in direction pattern in both datasets, some combinations have been tried and experimented to understand and then target these irregularities. Based on this explanatory study the correct matching combination of direction assignment for both datasets is chosen for conflation and is shown in table 3. For example, the 'Eastbound' and 'Northbound' traffic could be conflated to 'East' direction of LRS datasets, once the names and proximity tier have been taken care of. The combinations helped to overcome these irregularities in reporting the direction of road networks and the result was more accurate as compared to conflation which just focuses on the distance between two segments.

Table 3: Direction Combination

INRIX Direction	LRS Direction
EASTBOUND	E
WESTBOUND	W
NORTHBOUND	N
SOUTHBOUND	S
CLOCKWISE	E
COUNTERCLOCKWISE	W
NORTHBOUND	E
SOUTHBOUND	W
CLOCKWISE	N
COUNTERCLOCKWISE	S

This combination of direction was successfully able to cover the conflation of road networks from both the datasets with the desired accuracy. While doing an exploratory data analysis, the irregularities in the data became evident, apart from different choices of direction for the same road networks, there were some road segments which are not assigned directions at all. To target this anomaly, a new factor is added in the algorithm which is going to match the feature based on the bearing of the road segments. The next subsection talks about this methodology in detail.

Before getting into the specifics of this algorithm a comparison figure for a change in the number of INRIX segments before and after the first tier of automation conflation procedure is shown in figure 9.

In the current study, we compute bearings and assign directionality for road segments not assigned directions i.e., the segments which could not be conflated in the first level of conflation (right side of figure 10).

- **Conflation using the bearing**

The segments which were not captured by the aforementioned conflation process were attempted to conflate again using the bearings of an individual road segment. The methodology can be better understood once the definition of bearing is grasped properly.

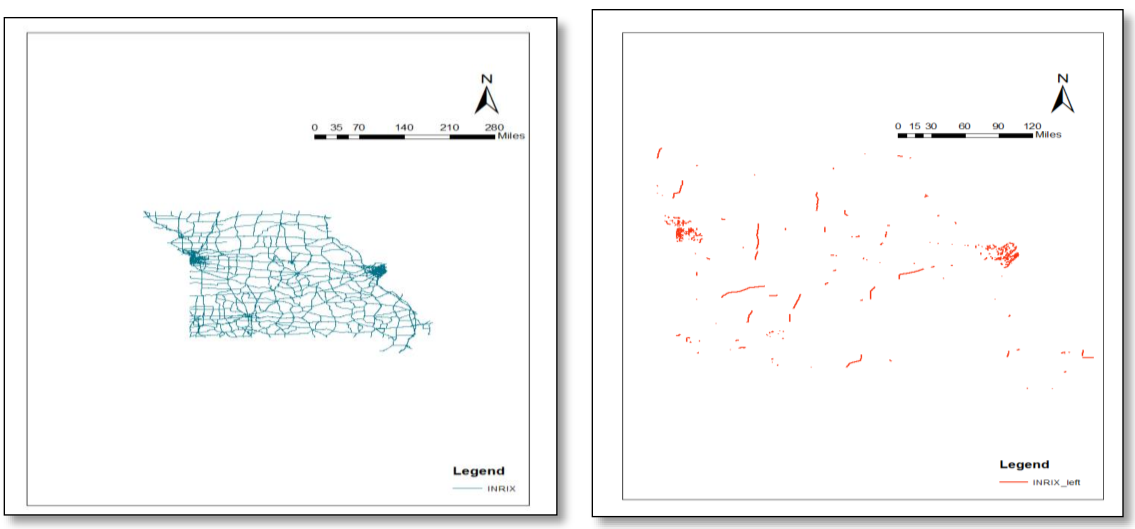


Figure 9: INRIX segments before and after the first tier of conflation

- **What is Bearing?**

The bearing for a road segment can be considered as the angle of a line measured in a clockwise direction to reference the North axis. As shown in figure 9, the bearing of line OP is x which is equal to the angle made by the line from the North axis in a clockwise direction. The bearing of a line helps in the determination of the direction of the selected segment.

This concept of bearing has been used as a theory for determining the direction of road segments for the conflation of left-over road networks from INRIX to the LRS data set.

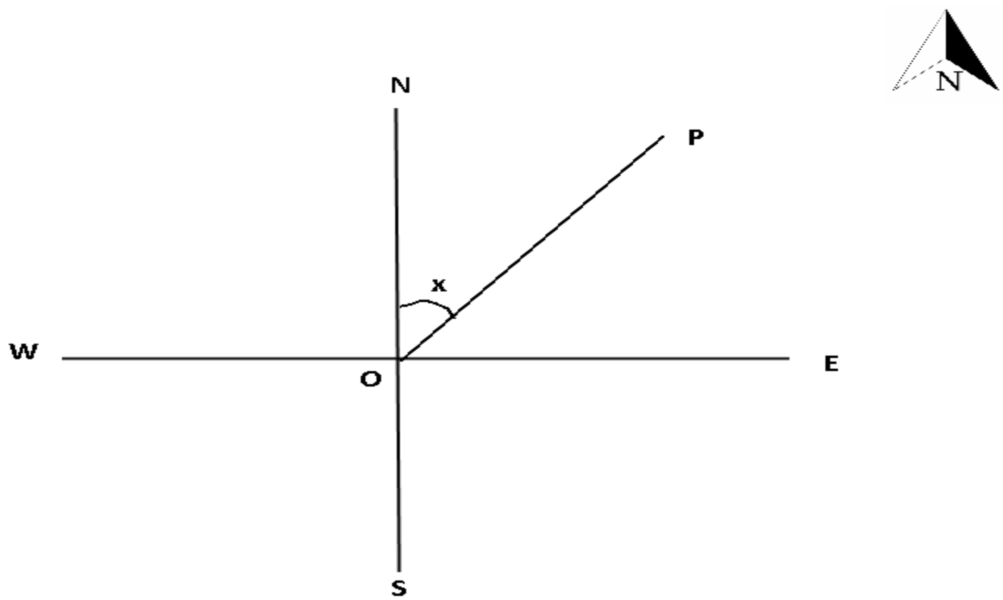


Figure 10: Bearing of a line

Feature Matching

One of the important aspects of the successful implementation of the feature matching process was the conflation radius. After attribute matching, a conflation radius has been decided on the basis to make sure the system is looking for matching features in the specified radius with the intention of decreasing the computational feasibility. The radius is chosen based on the trade-off between conflation rate and accuracy. The accuracy of the conflation rate was maintained by filtering the data based on the road name and direction of traffic assigned to respective road networks in both data sources, from the attribute matching process. Various conflation radius was experimented to attain a maximum conflation rate between LRS and INRIX segments. A graph between increment in conflation rate with respect to experimented conflation radius for Missouri Interstates is shown in figure 11.

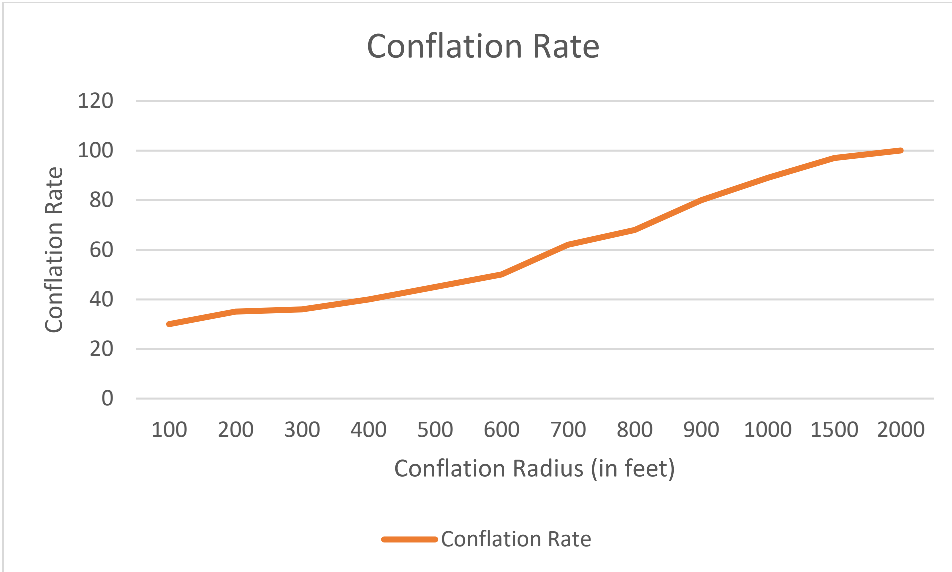


Figure 11: Conflation Rate for Interstates

From this trialing of multiple values of conflation radius, the radius of 2000 feet seemed to be an ideal choice and gave the maximum conflation rate. A sample of conflation for the Interstate network from both the sources is shown in figure 12.

The maximum number of segments was conflated using this algorithm, however, due to some missing information in LRS and INRIX segments, there was a small volume of segments which could not be conflated. This loss of data in the conflated segments could be due to several reasons it could be due to missing road segments' names, or the distance between the similar feature is spatially misallocated or error in data entry, etc.

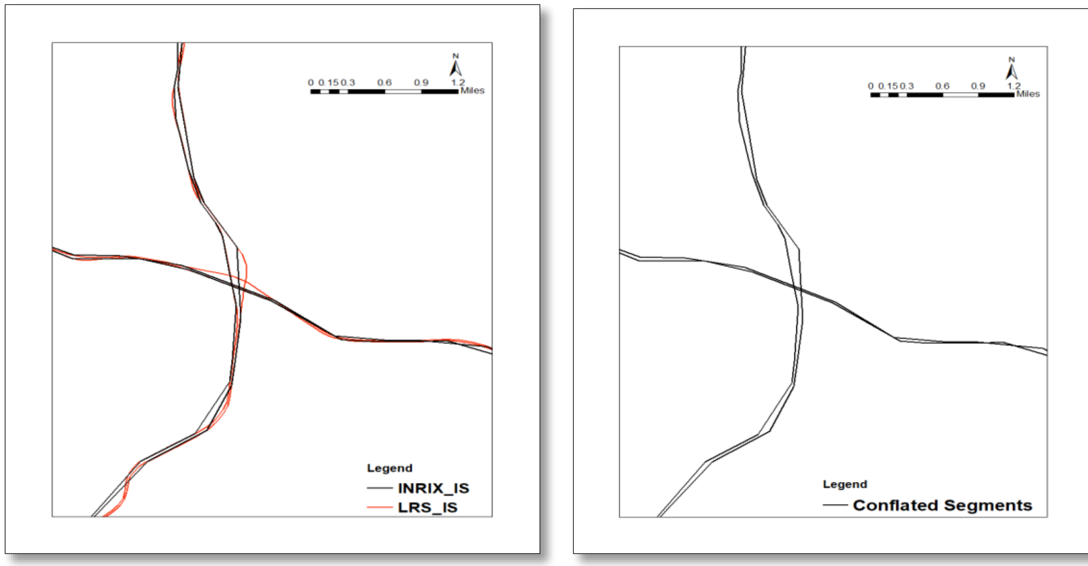


Figure 12: LRS and INRIX conflation for Interstates

The capturing of the left-over INRIX segments done in the following steps:

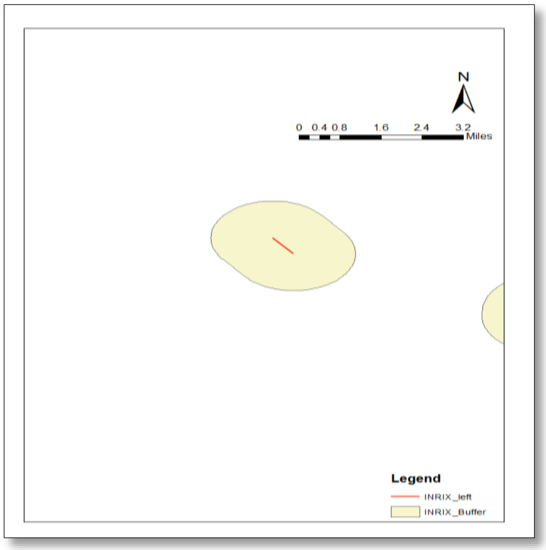
- Since these are the segments that have some irregularities in the data entry, a method based on the spatial location is preferred instead of relying on road network information for feature matching. An algorithm is designed in such a way that it creates a buffer of a certain radius is around each and every INRIX segment length to capture LRS segments in the vicinity of that particular segment.
- The following rules are then used to reduce inconsistencies in directionality assignments.
  - Rule 1: For each road segment in both layers, if the assigned directions match and the difference in the calculated bearing is less than 45 degrees, assigned directions should not be changed.
  - Rule 2: For each road segment in both layers, if the assigned directions do not match and also not opposite (e.g. N and E) and the difference in the calculated bearing is less than 45 degrees, re-assign directions in both layers as “NE”.

Similarly, for “South” and “West”, reassign as “SW”.

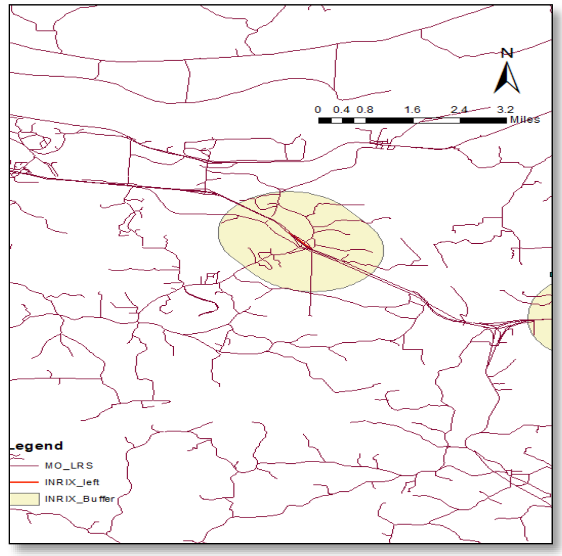
- Rule 3: For each road segment in both layers, if road directionality is not assigned, however, the difference in the calculated bearing is less than 45 degrees, assign directions in both layers as “A-D” (Assigned Directionality).

A detailed representation of this set of procedures is shown in figure 13. In figure 13(a) buffer size of the desired radius is drawn. Then this buffer is intersected with LRS segments falling inside the buffer boundaries which is shown in figure 13 (b). The result of this intersection gives LRS segments and INRIX segments with a common buffer id which is visually represented as figure 13 (c). Now for the bearing conflation of an INRIX segment, rather than looking for each LRS segment in the conflation radius, the computer is going to restrict its search to buffer size and number of LRS segments belonging to that particular buffer.

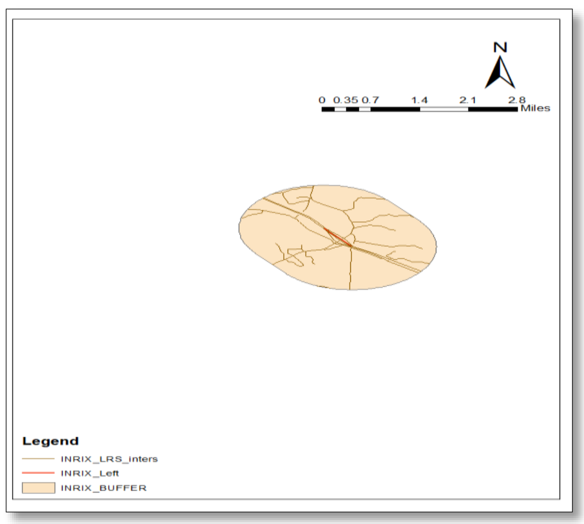
- After the intersection of two layers, now every INRIX segment will have a bunch of LRS segments around and out of which one of them is the matching feature for the INRIX segment. To find the matching feature the bearing of the INRIX segment is used as a matching criterion. The bearing of each INRIX and LRS segment is calculated based on the starting and ending longitudes and latitudes. This bearing value is then used for matching features from both the sources. The search radius of the buffer is selected based on the tradeoff between the conflation rate and conflation accuracy represented in figure 14. Based on this 6m buffer radius seemed to be optimum with a balanced tradeoff between conflation rate and accuracy.



(a)



(b)



(c)

Figure 13: Feature matching using bearing

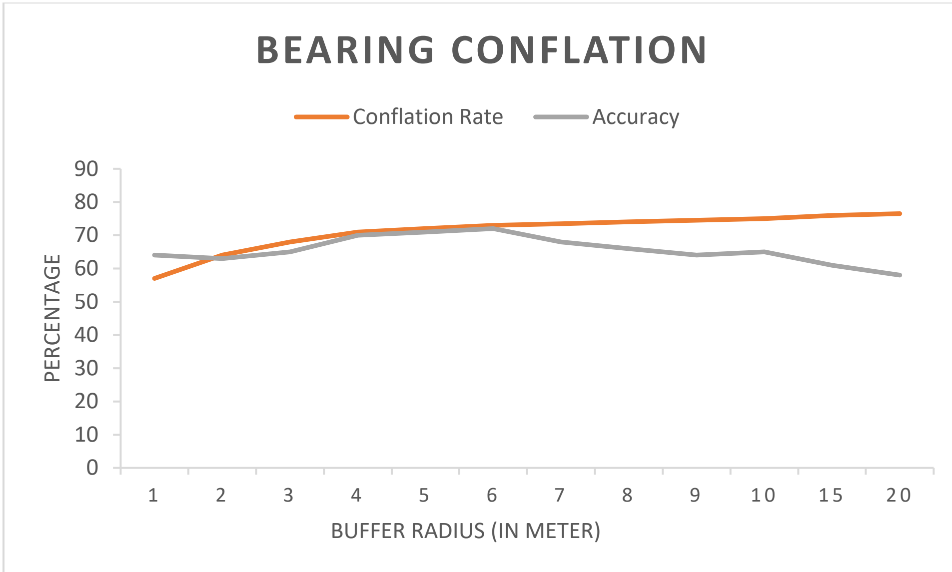


Figure 14: Variation of Conflation Rate and Accuracy with respect to the search radius

For this analysis, various functions from the **arcpy** library were employed. For the creation of a buffer around the INRIX segment the function "buffer_analysis." The code was run for the buffer values from 1 meter to 20 meters and then the buffer was intersected with LRS. Every buffer will have a unique id which would be common for both the segments INRIX as well as LRS after the intersection.

Within the buffer, the INRIX segment was conflated to LRS based on the matching bearing.

After accumulating a similar feature, a near table was created for every INRIX segment using the function "GenerateNearTable_analysis" from **arcpy** library and the feature is matched based on the nearest matching feature.

After finalizing the criteria for matching the features, the designed methodology uses near table approach to match the feature from the INRIX layer to the LRS layer. Hence, the matching feature criterion is based on two tiers for this approach:

a. Firstly, the segments are conflated based on the name as well as directionality from the LRS dataset for a selected INRIX segment.
b. The segments which didn't have directionality feature were simply conflated based on the bearing proximity within a selected radius.
c. Then the feature is matched on the spatial proximity of INRIX segment among the accumulated LRS segments using Near table approach

Since this approach uses multiple criteria to match features rather than just being dependent on the spatial location of road segments the accuracy achieved through this process was higher than the ESRI's aforementioned process.

Transfer Attributes

The attribute is then transferred to the base layer (LRS layer in our case) as mentioned for traditional GIS toolsets. The sample from the result is shown in table 4.

Table 4: Transfer Attribute Output Table

INRIX_ID	INRIX_NAME	LRS_ID	LRS_NAME
119P07741	US-36	85923	36
119+16858	WORNALL RD	1644975	WORNALL ROAD
119+07741	MO-10	85923	36
119-06674	MO-34	591824	34
119-04685	I-70-ALT/I-670	976285	WYOMING ST TO IS670W

It is evident from Figures 11 and 12 the conflation has been achieved of a decent rate and from table 4, it was apparent that the tools were able to conflate correctly even when the segments have a slightly different name. For example, I-70-ALT/I-670 from INRIX was able to conflate to WYOMING ST TO IS670W in LRS irrespective of some discrepancies in the name.

3.2 INRIX and Transit Conflation:

INRIX-Transit- The second pair of data sets used here are the INRIX (probe) layer and transit data collected for Saint Louis County. This conflation of probe road networks with the real-time location of transit data helped in getting traffic conditions on the Missouri road networks. Traditionally, this kind of network analysis for traffic parameters like delay, travel time, the queue length is usually done manually, as this conflation needs multi-level analysis before dealing with actual conflation. Here the INRIX data was conflated with the transit data collected from the Saint Louis County using the mile marker points and location of the datasets. This transit data comprises of busses' live locations for two weeks which contains variables like travel time of the trip, direction, name of the route, etc. Based on the time stamp and a unique trip id assigned to a transit system the travel time of each trip was calculated using the distance of the route.

USE CASE: The INRIX data provides travel time for each segment. To get the delay for a given route, firstly INRIX segments are conflated with the transit data and then the average travel time on each route was calculated by summing all the conflated INRIX segment's travel time for every trip. And then the delay was calculated by getting the difference between actual travel time take by transit and average travel time provided in the INRIX data. The overlay of INRIX and transit data is shown in figure 15 and on the right, the resultant conflated map of INRIX with transit data is shown. The conflation achieved through these two data sets gives traffic-related attributes on road networks.

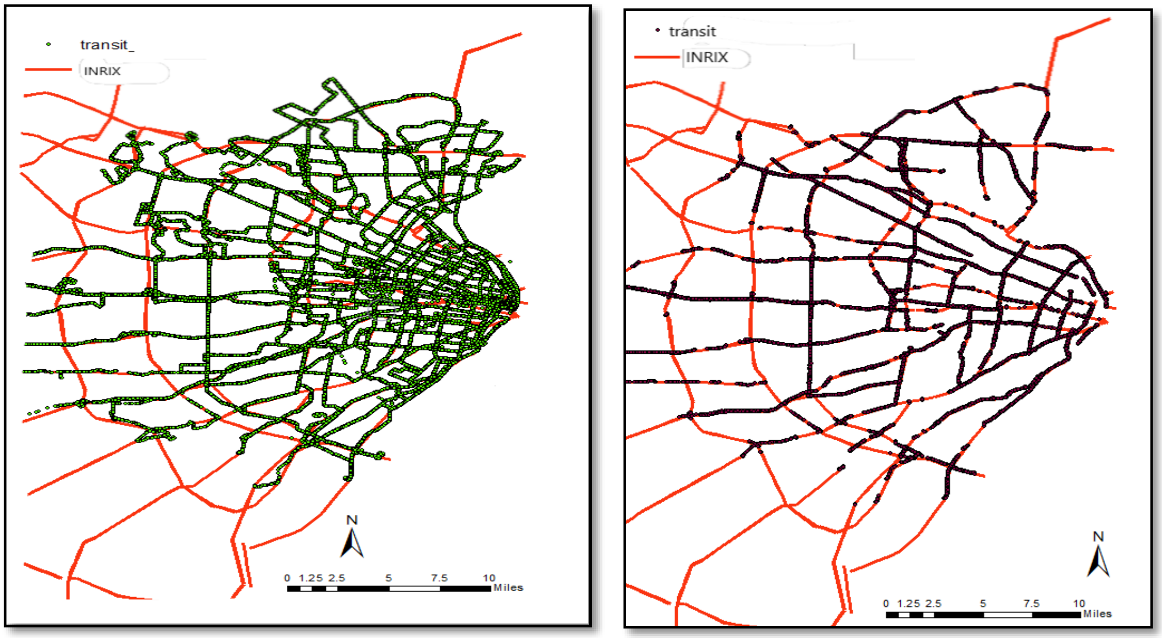


Figure 15: INRIX Transit Overlays and Conflation

3.3 INRIX and Detector Conflation

The conflation of probe data with traffic detectors at various points of Missouri road enriched the INRIX data with an important traffic flow parameter, which I, total number of vehicles at a given point i.e., traffic volume.

The conflation is achieved based on the theory of conflation theory of proximity of detectors with the closest mile marker and then from there to respective probe segments; the common parameter of mile marker used as the location of detectors on the road segment is conflated with road networks and all the data collected from detectors were combined to respective INRIX road segments. Here for a given route name and traffic direction, an INRIX segment is selected and divided into mile segments. Once the segment is divided into multiple sections using mile markers, the detector data is conflated to that particular segment using the location of detectors.

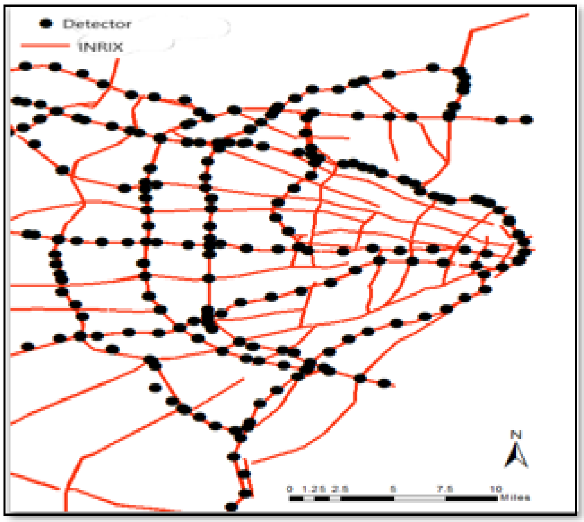
USE CASE: This amalgamation of traffic measuring parameter with the calculated delay variable can say a lot about the traffic movement on the route, for example, whether the delay is controlled or uncontrolled. It also would help to assist to find ways for the mitigation of congestion based on the understanding of the factors behind a delay. The conflation rate achieved was for fewer segments as it is due to few numbers of detectors and the sparse placement of detectors on the roads as shown in figure 16.

3.4 INRIX-Crash

To add a factor of route safety on the INRIX layer, the GIS data from INRIX is merged with the crash data reported multiple years available from MO_DOT. The crash was reported using the position of mile marker on the road. Similar to detector conflation, the merging of data has been achieved using this mile marker location as the primary criterion for the conflation, the data was fused with road segment data.

The crash data consist of the specific information of the accident reported with the type and loss of life or damage of property. Based on the type of loss and severity the safety of the route is ranked from 1 to 4 where 1 being the safest. The crash data and probe data conflation achieved a good conflation rate. The INRIX layer and the conflated route segments with the route safety factors are shown in figure 17.

USE CASE: The final layer after the conflation with multiple layers would have information merged from all layers, the INRIX segments with crash analysis, volume analysis, and traffic movement analyses are then integrated back to LRS segments. This final layer would have all the information from several layers, this data will not only be spatial accurate, but it will also carry the traffic-related values on the respective networks. These fusing and merging of data were fully automated and didn’t require any sort of manual analysis. The accuracies achieved were pretty satisfactory and the performance and time consumption of these algorithms were at par to some of the currently available algorithms.



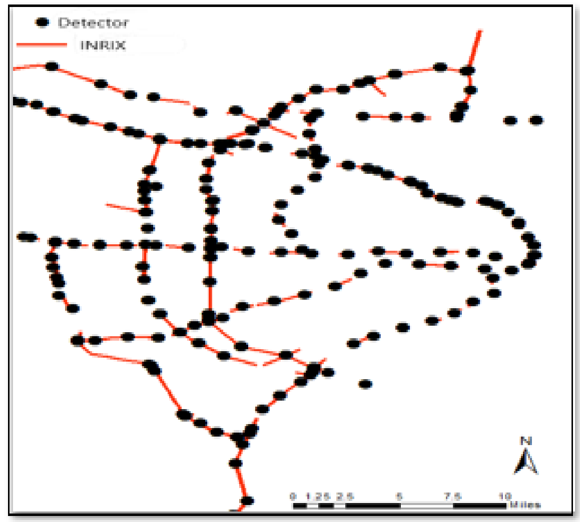


Figure 16: INRIX Detector Overlays and Conflation

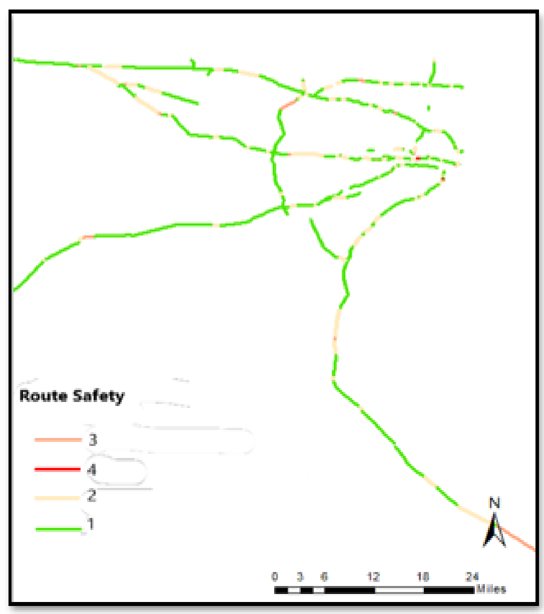


Figure 17: INRIX Crash Overlays and Conflation

CHAPTER 4 RESULTS AND DISCUSSION

4.1 Data description:

The data involved in this research work includes-

- INRIX data,
- LRS data
- Transit data
- Detector data
- Crash data.

INRIX data- This layer of the road network has been collected from the MO_DOT RITIS source. The data contains more detailed information about Missouri road networks, for example, the information like name, length, and the traffic directions of the routes. A sample of data is tabulated as table 5. This data gives travel-related data like travel time on each segment, distance miles, location, etc. The data contains road information of thousands of miles as 18,962 segments for the whole Missouri state.

Table 5: INRIX data set

TMC	ROAD	DIRECION	COUNTY	MILES	…
119P19179	11TH ST NORTHBOUND/11TH ST NORTHBOUND	EXIT 39B	ST. LOUIS (CITY)	0.146498	…
119P19220	BRANCH ST	EXIT 248B	ST. LOUIS (CITY)	0.096197	….

The only drawback this data has apart from some data irregularities is the coverage of road networks. This source of data covers a very small percentage of road networks**.** MO_DOT is constantly updating its road network coverage throughout the year. Currently, INRIX XD data covers a total of 18,962 segments in the state of Missouri. The INRIX data is also known as probe data and both the names are used interchangeably in this research work.

LRS data - On the other hand, this source contains data of road network collected from US Census Bureau TIGER file 2016 has information like names, county, and basic geographic details. This data has, undoubtedly, covered a higher percentage of roads of Missouri, from local streets to interstates, nevertheless, it lacks detailed information like the travel time, road orders, etc. A sample of data is shown in table 6 MODOT releases a new version of the LRS every quarter. The current release has a total of 611,285 of road segments.

Table 6: LRS data set

AAT_ID	COUNTY_NUM	NAME	DIRECTION	Shape_Leng	…
769944	106	DAVIDSON LN		394.022	…
727328	106	CIMMARRON RD		14.0569	…
1546068	108	1497		188.427	…
1583879	101	426		814.687	…
1583035	101	493		387.844	…
1583032	101	458A		383.096	…

A comparison of both data sets viz. INRIX and LRS are shown in figure 18. This diagram shows the difference in the magnitude of coverage of Missouri Road networks for both the datasets.

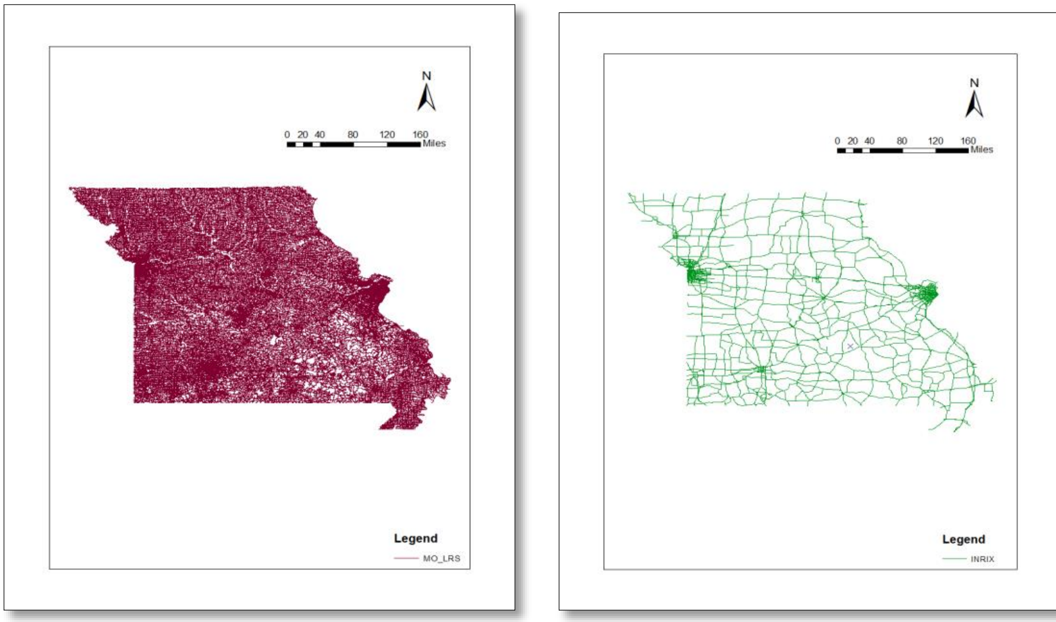


Figure 18: LRS and INRIX road networks

Transit data-This layer of information possesses tracking data of the transit system in Saint Louis county for three days in a week for two consecutive weeks viz. from June 19th to June 26th, 2019 collected from General Transit Feed Specification (GTFS). The collection of data has been done by calling API every 30 seconds and collected for three days in a week for two consecutive weeks. This data brings the location of the transit system on the road network with real-time location, timestamp, direction which helped to get an idea about the traffic variables on the network for a given route and direction. A sample of this data is tabulated under table 7.

Table 7: Transit data

vehicle_label	trip_id	route_id	travel_time	direction_id	route_long_name	…
32 ML King - WEST	2550658	15525	56.01667	0	ML King	…
32 ML King	2550658	15525	56.01667	0	ML King	…

- WEST						
32 ML King - WEST	2550658	15525	56.01667	0	ML King	3

Detector data- The traffic data collected from the 555 detectors placed in the various highways comes along with the vehicle count, interstates name collected from the Missouri Department of Transportation (MODOT). The count of vehicles from every detector in the data helps to understand the traffic flow on the respective conflated path. The mile marker, traffic directionality and the name of the road where the detector is placed made the conflation rate high as well as accurate. Delay calculated for every segment can be categorized under controlled or uncontrolled based on the vehicle count for that segment made available through this resource. The sample of this data is shown under table 8.

Table 8: Detector Dataset

detector	StreetName	Direction	Longitude	Latitude	Log
MI064E000.7U	I64	East	-90.8286	38.80161	0.7
MI064E002.0U	I64	East	-90.8113	38.79101	1.98
MI064E003.2U	I64	East	-90.7914	38.7794	3.2
MI064E004.6U	I64	East	-90.7717	38.76682	4.6
MI064E005.6U	I64	East	-90.7582	38.75364	5.6
MI064E007.1U	I64	East	-90.743	38.73782	7.13
MI064E008.5U	I64	East	-90.7262	38.72309	8.49
MI064E009.1D	I64	East	-90.7043	38.7141	9.1
MI064E009.8D	I64	East	-90.6916	38.7118	9.8

MI064E010.0D	I64	East	-90.69	38.7118	10

Crash data – this last traffic history database collected for Missouri's roads helps to visualize the road segments from the safety point of view. The crash data congregated based on the mile marker has the details of accidents like type, severity, conditions during the accident as well as the environment around like road surface, visibility, weather, etc. The severity of an accident can be pointed out based on the number of factors like vehicles involved, whether it was loss of property or life, etc. This data has been collected from state DOT for the analysis.

This conflation of these datasets with Probe and subsequently with LRS developed the conflated layer with analyzed traffic data variables like travel time, route reliability, traffic volume, etc. At the time of writing this report, the most current versions of both data layers (IRIX and LRS) were used. In the following section, we evaluate the effectiveness of the conflation approach developed for this study.

4.2 Conflation Result Discussion

Probe with LRS – this conflation aimed to enrich the LRS layer with the information of roads found in probe (INRIX) layer like travel time, the direction of traffic, and other routes related information. Nonetheless, due to the diversity of the datasets, this conflation required special attention. Rather than conflating just based on the spatial parameter, this algorithm addressed the issue of data anomaly and inaccuracies by taking consideration of route configurations. By matching the attributes of the county, road name, and traffic directionality of the matching feature and then conflating based on the location proximity of matching features from the near table boosted the accuracy as well as the conflation rate. Since the attribute chosen for roads was unique the mis conflation was zero, this code was tested for all the interstates for Missouri state and gave the results as shown in figure 19. The perfect accuracy attainted for interstates was mainly due to high similarity in the nomenclature adopted for the interstates designations, for example, LRS uses the number of interstates as road names while Probe data uses the number of interstates with "I". So, in LRS Interstate 29 is presented as "29" on the other hand in probe data it is labeled as "I-29." The algorithm of text similarity was able to capture this minute difference and hence the accuracy, as well as the conflation rate provided, was so high. The conflation rate was 98.9 % with 100% accuracy.

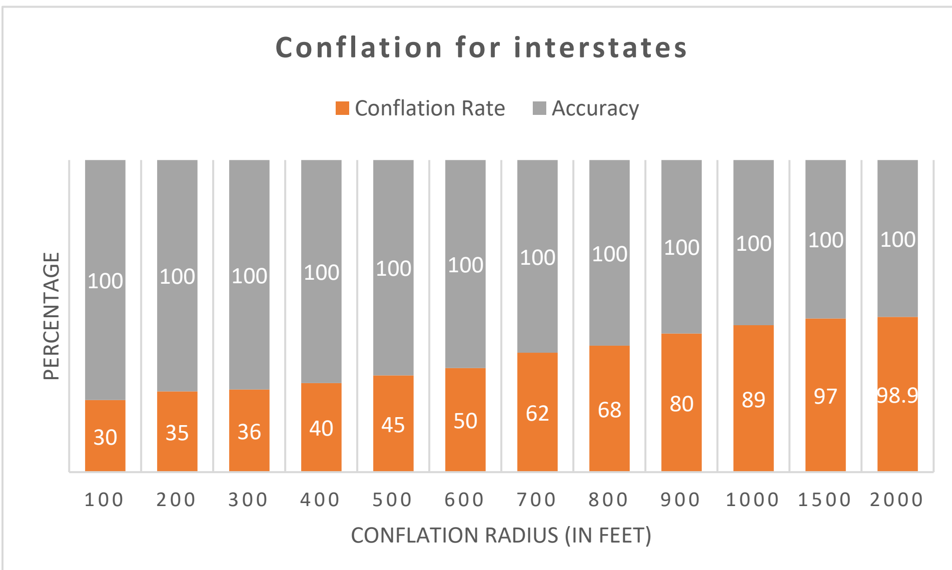


Figure 19 Conflation Rate and Accuracy for Interstates.

On the other hand, when this conflation was tried for whole MO road networks, the overall conflation rate achieved was 86%. The lack of conflation rate was mainly due to missing attribute features such as traffic directionality or names as well as limitations of text similarity algorithm which was unable to detect subtleties in the way nomenclature was adopted.

For such conflation, a more sophisticated tool was employed instead of just being dependent on spatial proximity. After the creation of buffer around every Probe segment and intersecting with surrounding LRS segments, the algorithm uses the concept of bearing to conflate the similar segment. Since this tool was more advance than spatial conflation, it was able to achieve higher accuracy as shown in figure 20. The accuracy achieved was 72% with the trade of conflation rate of 73%.

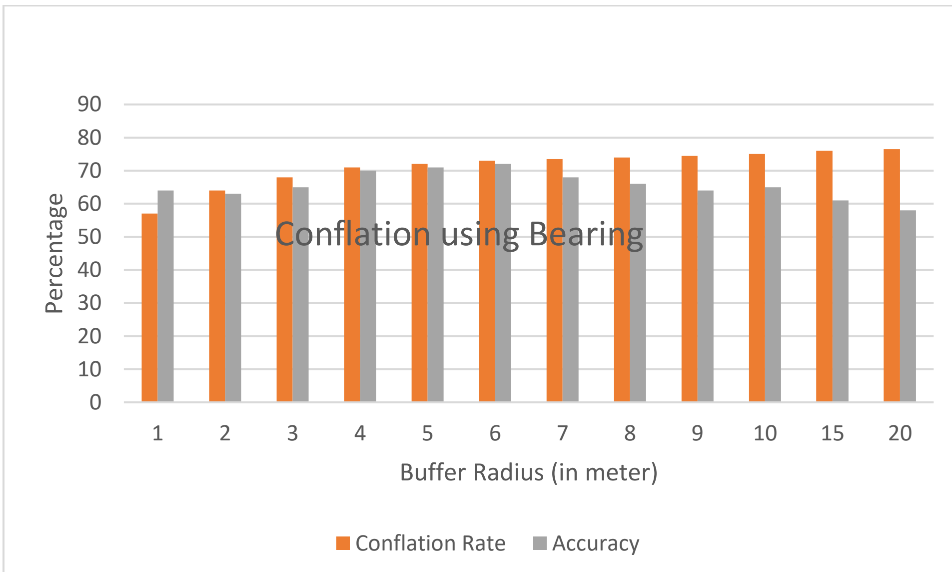


Figure 20: Conflation rate and accuracy for bearing

Due to the high dependency on physical aspects of data, the conflation rate achieved was decent and the accuracy was adequate. The conflation rate, as well as accuracy of few selected segments, were tabulated under table 9. The dip in these parameters was mainly due to lack of data and mis conflation, since there were no governing attribute parameters, the mis conflation was pretty high.

The higher accuracy achieved for certain segments was mainly due to proximity as well as similar laying of the shapefiles, however, certain segments were mis conflated or not conflated have many factors attached for such outcomes. The details for this table are discussed in the conflation discussion.

Table 9 Conflation rate and Accuracies for few Major roads

Road Name	Conflation Rate	Accuracy
Airport Road	0.947	0.647
ADELAIDE AVE	1	1
CLARK AVE	0.03	0
LACLEDES LANDING BLVD	0.01	0
FOREST PARK PKWY	0.2	0.09
IS44W TO IS270E	0.24	0.04
IS44E TO LAFAYETTE AVE	0.1	0.06
BROADWAY TO IS64W	0.32	0.04
N AIRPORT BLVD	1	0.69
STADIUM BLVD	1	0.79
WYANDOTTE ST	1	0.85
S JEFFERSON AVE	1	0.91
WILSON AVE	1	0.714
WESTRIDGE RD	1	1
US-54-BR/MARKET ST	0.48	0
N ELSON ST	0.9	0.14
W 39TH ST	1	0.8
WALNUT ST	0.98	0.93
W KANSAS ST	0.6	0.5

Probe with Transit - this conflation was done to gather traffic variables for the different routes. The live location of transit was conflated with the Probe layer to enrich the road network with traffic data like travel time, average speed, route credibility, etc. All the INRIX segments are gathered for a unique trip id based on the conflation. The average time given for individual probe segments is gathered and averaged for that particular trip. The distance was calculated based on the miles per trip gotten from the summation of conflated probe segments. The timestamp given for a trip gives an actual idea about the actual travel time taken for that trip, on the other hand, probe data gives on an average time that should have taken by the vehicle on that segment. The difference in the travel time of these two datasets gives the traffic flow parameters like delay, travel time credibility, etc. An interactive dashboard that can be generated using the fusion of this data is shown in figure 21. The overall accuracy achieved was 85% for these datasets. Since the study was only considering Saint Louis County, the interaction of all the probe segments with transit data couldn’t be captured.

Probe with detector - The probe data is conflated with the detector file separately and the layer

has been enriched subsequently with the information gathered from the detectors at the various locations in Missouri. The detector data contributed vehicle count related to the traffic flow on respective positions which subsequently conflated with the INRIX layer making the respective road network supplemented with traffic data like traffic volume with the direction of the traffic. The basic common variable for this conflation was the position of detectors found out by the mile marker. This conflation eventually merged with LRS_INRIX conflated to transfer the data to the resultant layer. The accuracy of conflation has been modest with a value of 80%. The less accuracy of these datasets mainly due to the sparse placement of detectors (mainly on Interstates). The traffic volume achieved can be fused with travel time could give a brief idea about travel time credibility as well as congestion type. Such an analysis is shown in figure 22.

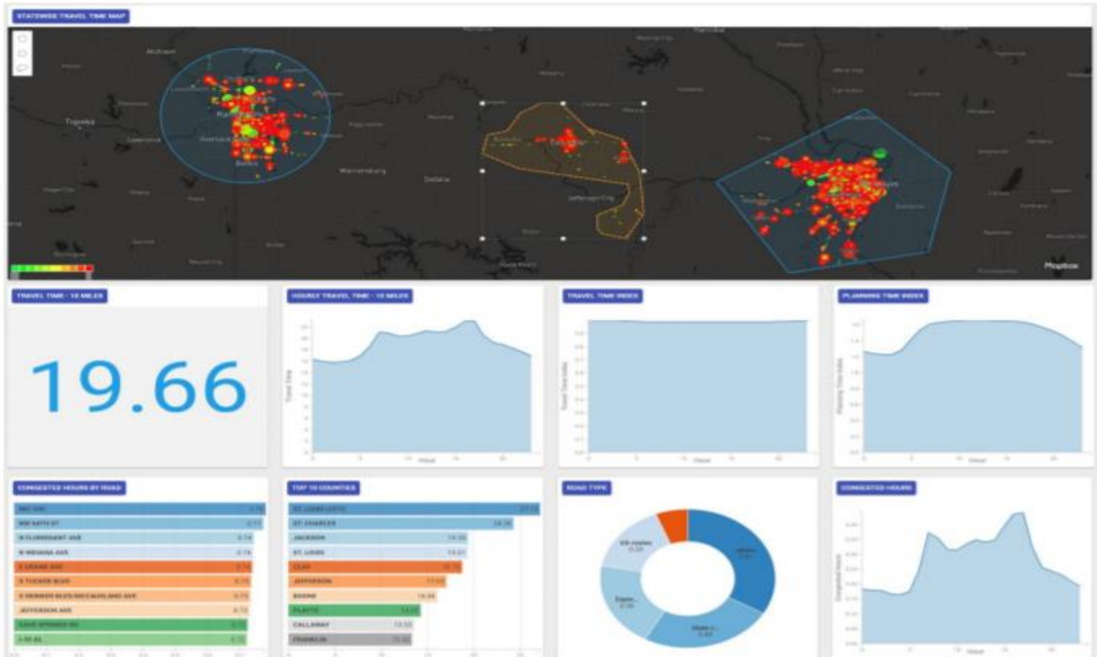


Figure 21: Travel time interactivity

Figure 22: TITAN Interactive Dashboard for exploring statewide mobility

Probe-Crash - The crash INRIX conflated data helped to add a factor of route safety on the map.

Based on the route safety factor the route choice and demand of the segments could be used while dealing with the travel model. The safety number assigned to a route dependent on factors like the number of crashes, type of crashes (KABCO- fatality, property damage, etc.) This route safety could have also been used to get an overall safety analysis of Missouri road networks.

Eventually, this conflated probe data with traffic as well as crash data are conflated with LRS to achieve the final layer of road segments with augmented information of the routes as well as the expected travel experience parameters like travel time, delay as well as the route safety based on the previous accidents. The accuracy of the respective conflation is tabulated in table 10.

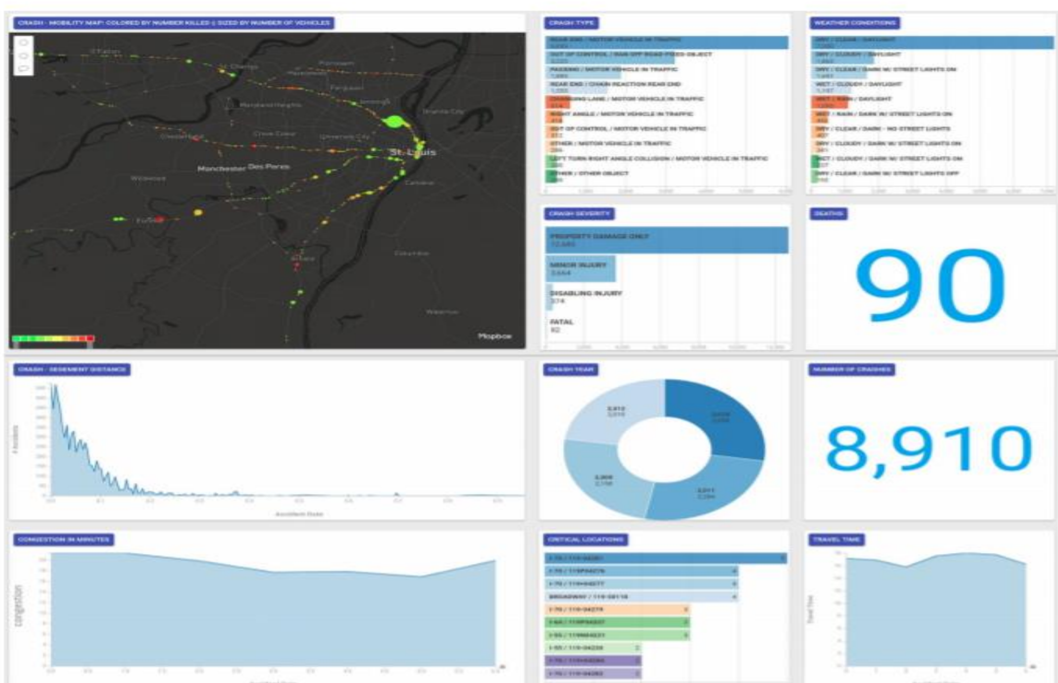


Figure 23:Statewide safety mobility dashboard

Table 10: Conflation Rates for the various layers

S.No	**Conflation**	**Accuracy**
1	INRIX_Transit	85%
2	INRIX_Detector	80%
3	INRIX_Crash	80%
4	LRS_INRIX	95%
5	GIS LRS_INRIX	48%

With this reasonable accuracy for multiple merging of layers to get a final map with improved spatial data as well as relevant traffic variables, the desired layer of LRS with the aforementioned data is achieved. The data shared in table 11 gives an idea about the information the final layer is going to possess after conflation through all the conflated layer data.

A superimposed image of all these layers and the visualization of one of the parameters for these datasets viz. delay is shown as in figure 24.

After conflating all the data segments, a visual dashboard was created with the help of the tool OmniSCI. In figure 24, the parameter for travel time has been visualized. The color variation from green to red shows the increase in the travel time for Saint Louis County obtained from the transit data set. This software gives on-click visualization and analysis for all the parameters involved and could help immensely for the visualization of big data like this in the field of transportation engineering. The travel time parameter visualization in the figure categorizes road segments using delay parameter for the Saint Louis county; with the red being of highest delay and green with no delay. This kind of imagining of the conflated layer gives a quick idea about the current status of road segments with respect to parameters of interest.

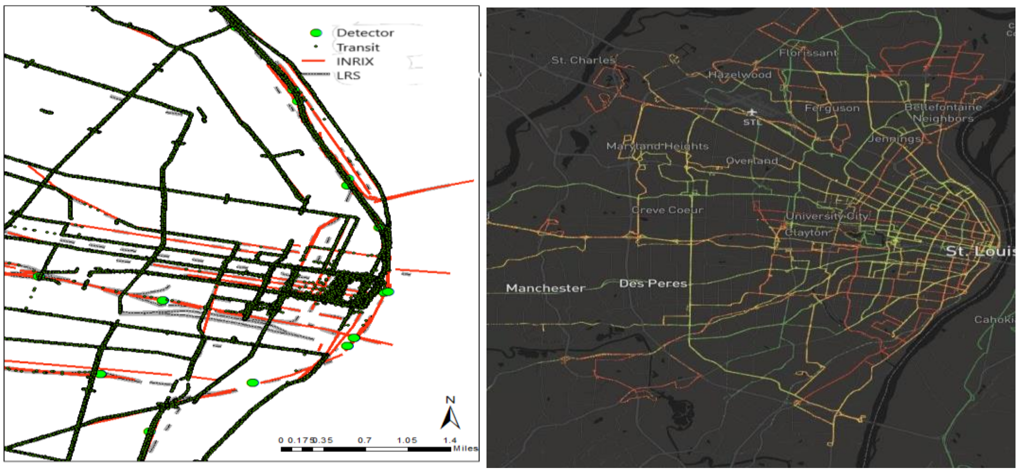


Figure 24: Overlay of all conflated layers and travel time visualization

Table 11: Final conflated layer

LRS_ID	CO	ROAD	DIR	INR_ID	MILES	Travel time	Delay	Volume	Route Safety
86647	11	US-36	E	119+07739	0.606	0.76	0.55	365	1
796991	13	US-36	E	119+0728	8.989	8.25	6.73	365	1

				3					
87197	11	US-54	E	119+0986 3	2.14	2.17	4	370	2
86658	11	US-54	E	119P0774 0	0.506	0.55	0.48	370	2
86953	11	US-60	E	119+0986 4	4.36	6.69	5	300	1
797013	13	IS-70	E	119+0986 0	10.76	9.78	7.21	370	2
87475	13	LP-70	E	119+0728 1	9.76	9.13	4.56	148	2
86239	11	MO- 150	W	119P07741	0.497	0.61	0.2	295	3
86970	11	OR- 150	E	119+0986 3	2.1	2.17	1.66	120	4
87269	11	US-36	E	119+0727 6	4.1	3.91	1.43	365	1

4.3 Challenges with the current results

One of the important challenges incurred during automating the conflation process, especially for such a big scale is a false correlation or false conflation. The workflow for map conflation developed in the current study also generates incorrect results in certain situations and these challenges could be mainly due to:

- Text similarity
- Bearing Error
- Segment lengths
- GIS errors
- Data error

Text Similarity- Another thing that has been unfolded through this study which was hindering the conflation process significantly was the difference in the data labeling. One of the most basic challenges faced during the merging of information from different sources is the variance between the ways the nomenclature has been implemented. Although the data has the same geographic features and locations, it still fails to get conflated or mis-conflated due to the absence of standard formatting of labels. The most common one is the difference in the name of the same features; different sources have their unique ways to store the information. Basic things like “-”, “,”, “.”, spellings, abbreviations become a great obstacle to overcome during conflation, especially, when the data is big and complicated. The rectification of this issue demands robust computational power with precision to overcome these subtle nuisances which usually requires human intervention and hence making the overall process complicated and inefficient.

The table 12 shown here shows how certain subtleties in the name of the same road was failed to capture by the existing algorithm.

Table 12: Text name subtleties for certain major roads

INRIX_NAME	LRS_NAME
ARSENAL ST	ARSENAL AVE
BALLAS RD	SO BALLAS RD
BAUMGARTNER RD	OLD BAUMGARTNER RD
9TH ST	NINTH ST
ARENA PKY	ARENA PKWY
BIG BEND BLVD	BIG BEND RD

Conflation Radius - The conflation rates will be greatly improved with better feature recognition algorithms and similarity analysis. The distance within which conflation is carried out is another significant factor that influences the performance of the routine developed in this study. Increasing the distance threshold will correspondingly increase the number of XD segments conflated, however, the accuracy of the conflation results will be compromised due to wrong mappings between the two layers especially at road intersections. A shorter distance threshold, on the other hand, will produce the highest accuracy although the percentage of segments that will be conflated will be greatly reduced. In the current study, a varying distant size was used, however, this limitation of finding the "perfect" search radius size couldn't be properly addressed. The search radius definitely gives a boost in computational timing by limiting the search radius for computer, nonetheless, due to this some outliers are unable to be capture. Such an example is shown in figure 25, the selected segments for MO-291 is traced. It is evident from the diagram the distance between two segments from different sources varies greatly and to find a search radius size that will cover every part of this segment is tricky and requires more sophistication in the analysis. From this example, it is evident that there is still a dire need for efficient technologies that could overcome these distinctions required in search radius without any human involvement and with higher efficiency. Figure 11 and 13 shows the variation of conflation rate concerning varying search radius.

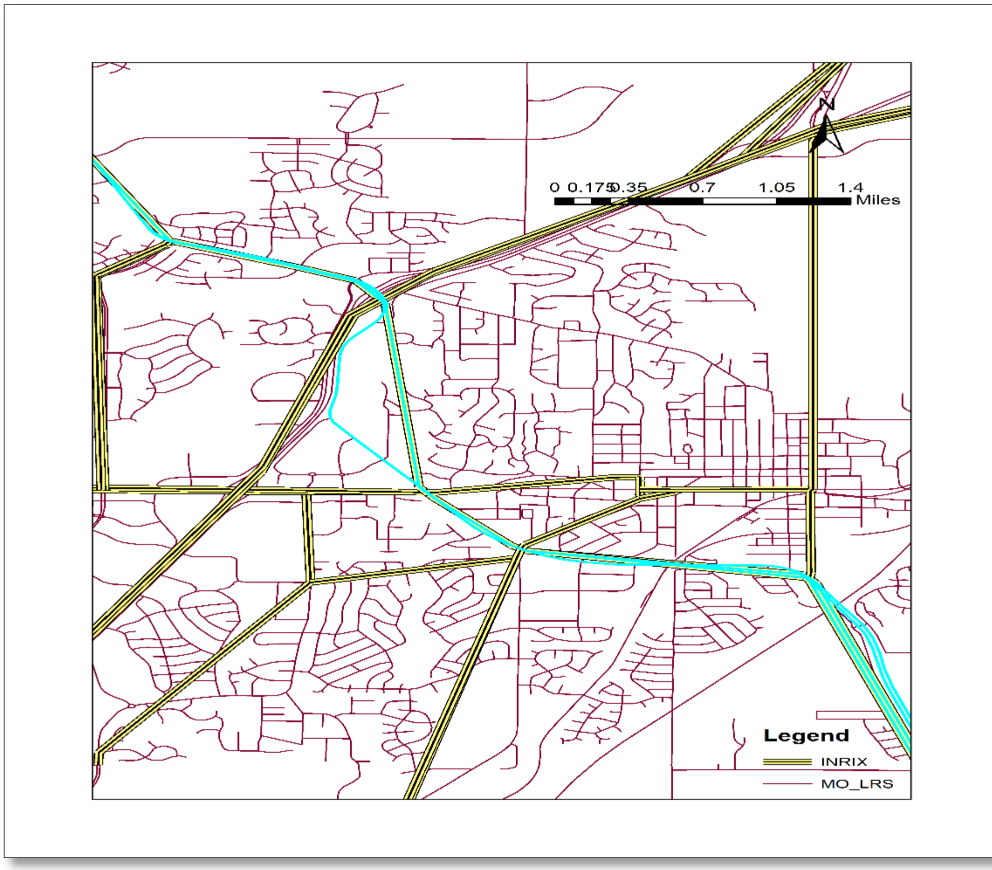


Figure 25: Variation in the distance between two matching segments

Bearing Error- While using the bearing for conflation besides proximity, there was an increase in the conflation rate and accuracy, however, it wasn't close to expected values. This hold in the values was mainly due to the lack of sophistication in the procedure. Although the conflation using bearing was doing a pretty good job but since there was no governing parameter of these matching features, the segments were getting conflated to nearby segments whose bearing lies within the 45° difference. An example of conflation using bearing for Kansas Street is given in figure 26; on the left side, Kansas street is selected for INRIX data and on the right side the selected segments which had been conflated for that street. If looked closely, the segments on the right were mis conflated to Kansas Street, even though the right segment was right there.

This limitation of bearing can be overcome if it has been coupled with some governing parameters like unique data information or some computational capability to assign segments based on more matching physical aspects like size, shape, direction, etc.

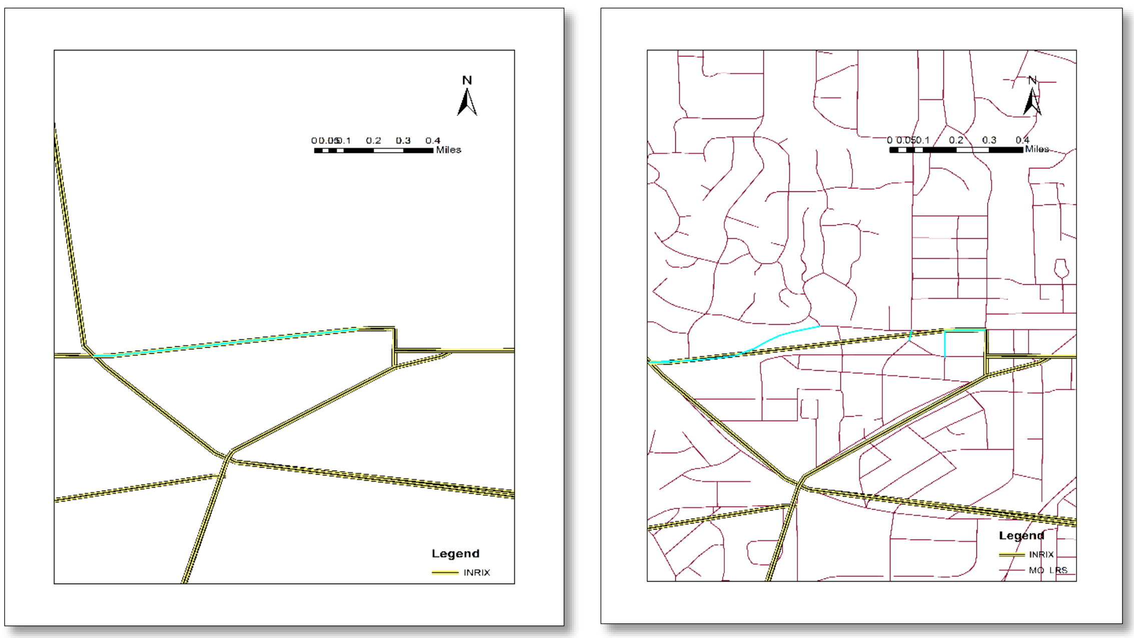


Figure 26:Bearing Conflation for Kansas St

Segment lengths- The conflation is primarily based on spatial joining of features from different map layers, and due to the presence of diverse form and shapes of road segments, this process becomes unusually challenging to achieve if targeting for an unbiased conflation between two features on large-scale data. The influence of segment length is much more when there is no other attribute feature addressing mis conflation. If a curve and straight segments are present close enough to a feature from another layer, the conflation could be challenged by the theory of proximity; the features would be matched based on the closeness rather than other authentic parameters like direction and name. Also, when the segment length is more and curvy it tends to mis conflate especially as the alignment of segments are constantly changing. When segments are very small, it loses the capability of individuality and gets conflated to any nearest segment. The influence of segment length in the conflation rate is shown in figure 27. This biasedness could be overcome by using more sophisticated computational algorithms that can differentiate between the subtleties in the segment length as well as shape.

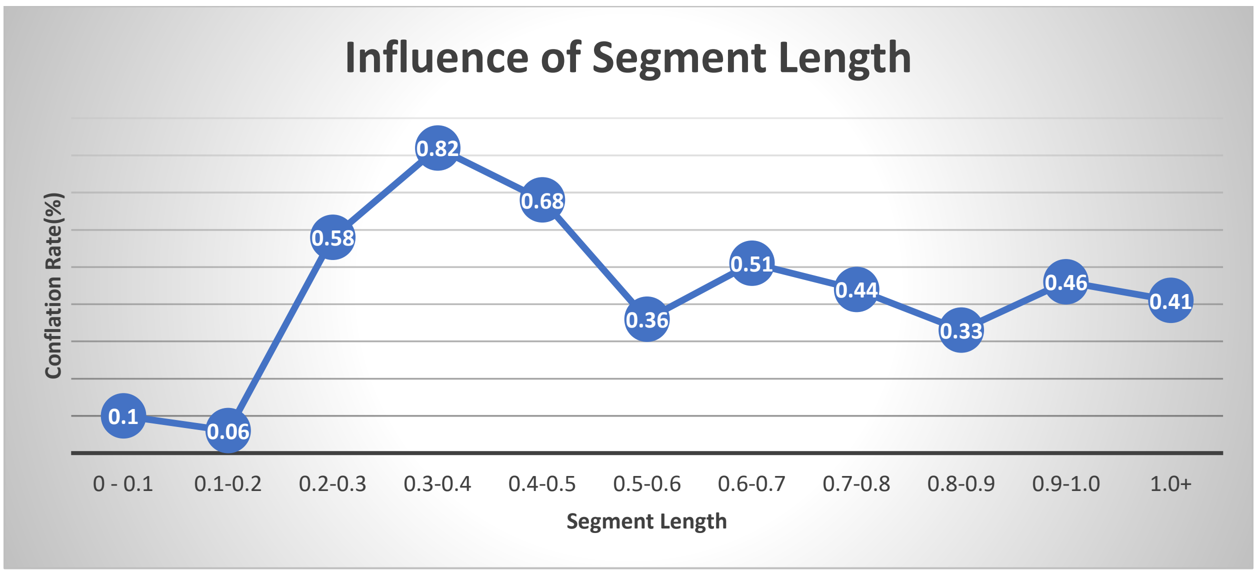


Figure 27: Influence of segment length in conflation rate

GIS errors- The improper position of geographies in the map layers is also another important contest encountered by researchers when it comes to merging the spatially different maps. These features are much more complicated and ambiguous especially when data have been gathered from numerous sources. These discrepancies become prevalent in geometric structures like highway interchanges, roundabouts with multiple ramps and winding roads probably due to the complexity of road networks and inefficient computational tools. These incongruities in the location of features could lead to false conflation and overall absurd information. This error was evident when testing the size of the conflation radius.

Data Issue: While dealing with data there were many issues with the reporting of information. This algorithm has tried to overcome such irregularities by filtering the data as much as possible. However, the issues like missing data and error in reporting the names of data were difficult to target. As there was no significant pattern in such errors it was hard to prepare a set of procedures targeting such issues. For example, Interstate 29 (I-29)in the INRIX layer was reported as US-21, then some routes had some segments missing, altogether. Figure 28 shows one such problem, in the LRS data is shown in highlighted blue color whereas the same I-44 is reported with some error in INRIX shapefile (on the right). Such types of issue were difficult to address and were one of the major reasons for hampering the rate as well as the accuracy of this conflation algorithm. This type of issue could be addressed through a sophisticated computational tool or some sort of artificial intelligence that can detect such manual errors.

Figure 28: I-44 from LRS and INRIX layer

4.4 Concluding Remarks and Recommendations

This project develops a methodology for the automatic conflation of two geographic data layers: TIGER's LRS and MODOT's Probe segments and extended to traffic data and crash data available for the state of Missouri. This work is sprouted to improve the overall effectiveness of the conflation process. Rather than confining the focus on improving specific geo-related information regarding routes, it was a good idea to take this merging process to different types of database to achieve a layer of map which has much more pertinent parameters which would help DOTs to keep an overview of all the road segments with respect to relevant parameters in return it would help in increasing the overall travel experience on these roads. So far, the calculation of specific traffic-related parameters was done manually and due to its complexities and the large dataset size, they were confined to specific areas of interest. Being said that, there were many aspects of conflation that have been unfurled during different phases of this project which needs attention to make this procedure much more productive. The protruding one would be a conflation of GIS data with traffic and crash data; although it has done a satisfactory job when it comes to bringing the traffic parameters in the spatial data and improving the overall quality of road segments, still lacks the complete effectiveness of these conflations due to meager precision. A slightly lower accuracy of these INRIX conflations achieved with different layers could be mainly due to the following two reasons:

- **Computational methods-** The technology available and the algorithm employed could be not efficient enough to overcome the nuances encountered during this process. For example, the GIS errors in reporting the crash data or sparsely uneven distribution of detectors, etc., could lead to poor accuracy. Nonetheless, these anomalies could be easily overcome by using an advanced and specific algorithm that takes on these different tones of data available out there.

- **Data-** The other prominent thing which had been tricky to handle was the diverse nature of all these data. Probably one algorithm is incapable of handling these varied forms of reports and database employed for achieving this conflation. This could be easily and significantly improved by advancing the data collection methods by the inculcation of technologies to improve the overall quality of data and minimize the false reporting of information as much as possible. At a conflation rate of 95%, there is still a lot of room for improvement. The following recommendations will be critical to achieving a more appreciable conflation rate.

- Considerable improvement in conflation rates can be achieved if robust pattern matching algorithms are used instead of relying solely on in-built ArcGIS feature matching models. There have been improvements in the development of spatial pattern matching algorithms recently in the open GIS community. Tapping into this resource will be useful.

- A thorough comparative analysis of all Esri's ArcGIS tools for map conflation should be conducted. In the current project, only the rubber sheet tool was explored. Other conflation tools were not explored and compared to the existing algorithm.

- For complicated features such as interchanges and roundabouts, this study suggests a manual procedure for the conflation process.

- A more consistent and unified framework for defining road segment directionality should be communicated to all vendors. Due to the inconsistent assignment of directions to road segments, the current study used the start and end latitude/longitudes (bearing) to recompute the directionality of each segment in both geographic layers. When conflating longer segments to shorter ones, computed directionality can be misleading. With the available tools and technology, this work was able to achieve satisfactory results and opened doors to achieve conflation for various types of databases which could help to eradicate the manual calculation of these parameters. Also, this work would encourage us to have these parameters analysis handy rather than make it available as per requirements. Nonetheless, a lot can be done to take this study to different levels and fields of transportation, especially, when it comes to handling big transportation data for the analysis of different variables.

- The handling of missing data could be handled more efficiently for example the uses of tools like mean substitution, regression imputation, last observation carrying forward, etc., could help to do accurate analysis even if there is an issue of data irregularities.

- Hashtable could be an appropriate way to achieve higher text similarity accuracy. By defining some common combinations in the hashtable the text-similarity algorithm can be improved significantly. Combinations like ‘PKWY’, ‘PKY’; ‘Avenue’, ‘ST’ etc., are some combinations that can be zipped using a hashtable. The choice of combinations could be better analyzed by doing some explanatory analysis of these combinations.

- **Accuracy-** The conflation accuracy achieved could be better justified based on the field where it has been implemented. The travel time, delay, route time credibility are some parameters that could be used in the field of traffic and can be used for the planning of future roadways as well. Higher accuracy is a requirement for the planning area as it defines policy for future development. The traffic flow parameters delay as well as traffic count could be employed to get an idea about traffic problems like the type of congestion, controlled or uncontrolled. Since the analysis has to be made from the current study, these areas require a more sophisticated tool to achieve a higher rate of conflation. On the other hand, conflation related to crashes gives some transportation safety-related parameters like route safety based on the type of crashes as well as the severity of crashes. The requirement of accuracy for this conflation is not tight and a decent rate is acceptable, however, further studies need to be coupled with the current conflation as the crash frequency is a sensitive parameter and supplementary research is a requirement.

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