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IDENTIFYING PHYSICAL AND MOBILE DMV LOCATIONS IN NORTH CAROLINA

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ABSTRACT

Growing population and changing demographics in North Carolina result in increased demand for DMV services, specifically for Real ID issuance. Considering the geographic distribution and the spatial characteristics of the demand, decision makers need to open new locations and/or reallocate limited resources among existing DMV locations to improve the operational efficiency and customer experience. The objective of this study is to provide an integrated approach for selecting the optimal DMV locations using expert knowledge, data mining, Analytic Hierarchy Process (AHP), Geographical Information System (GIS) and SAS Software. The proposed approach identifies sixteen location criteria through experts' input as part of the AHP process, yielding demographic attributes, flexibility, efficiency, cost and access to public facilities. Following the weight assessment for all criteria and sub-criteria, normalized weights are used for location suitability analysis in ArcGIS. Based on our projections for the demand and related geospatial data, alternative DMV locations are determined and visualized through ArcGIS. Finally, the alternative locations are evaluated by AHP weights and the multi-criteria location selection problem is optimized to maximize the coverage across the state.

INTRODUCTION

Federal agencies will enforce tougher security standards at airport check-ins, federal buildings, military installations and nuclear sites at the beginning in 2020. This requirement is posing a challenge against the NCDMV to plan enough locations to handle the increased workload in all parts of the state including urban and rural areas. One of the most important decision-making processes is to optimally locate new physical and mobile locations to address the demand of prospect customers. This is an important concern as these locations will face the influx of ID conversion applications to meet the NC Real ID deadlines.

Literature Review

One of the oldest problems facing businesses, particularly small ones, in marketing and operations management is where to locate organizations (Stevenson, Hojati and Cao 2007). The location decision is strategic with long term impact on an organization's capacity to serve its market and maximize benefits to the organization. Although globalization and emerging technologies, such as online retailing, change the way location decisions are made by many organizations, these factors have made location decisions even more important for brick and mortar retailers. A typical location decision involves identifying the market to be served by the facility, searching for potential locations, and then selecting the best site. This research provides a new twist on an established process.

From the earliest research (Hoover 1937; Czamanski 1981), location relative to customers has been identified as the central decision for industries including retailing (Reynolds and Wood 2010). Methods and technologies for doing so have become increasingly sophisticated and are essential to today's largest retailers as they select locations (Hernández and Bennison 2000). While most studies on location decisions are theoretical with a major focus on cost factors, Karakaya and Canel (1998) provide empirical evidence to determine the importance of various location-related variables for different industries (manufacturing, retail, banking, insurance, and consulting) and for different company sizes. Even small and moderately sized retail firms are often familiar with basic location techniques and are increasingly using geographic information systems (GIS) to support their decision-making, although they may not be able to afford the more sophisticated methods such as neural networks and expert systems (Reynolds and Wood 2010). The most advanced location analysis techniques are usually employed by high-tech, energy and manufacturing industries with an emphasis on the forward facility location problem (Clark and Rowley 1995; Ghadge, Yang, Caldwell, Koenig and Tiware 2016; Seyedhosseini, Makui, Shahangaghi and Torkestani 2016; Torkestani, Seyedhosseini, Makui and Shahanaghi 2016).

Typical focus on customer demographics & specific applications of facility location problems are studied by Clarke and Rowley, 1995; Clarke et al. 2003; Ghosh and McLafferty, 1987; Laulajainen, R., & Stafford, H., 1995. The literature on location analysis of nonprofits and government facilities remains an open area (Sirinesa and Shnoer, 2018).

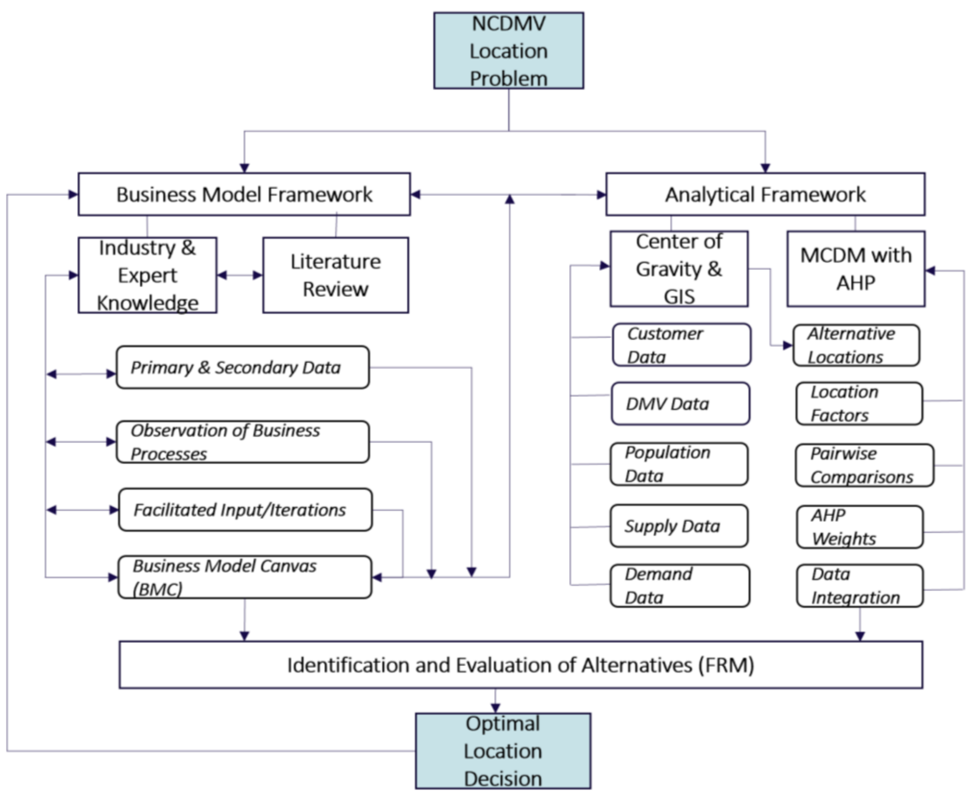


Figure 1. Expert Knowledge and Evidence-Based Location Methodology

METHODOLOGY

In this study, we utilized *Expert Knowledge and Evidence-Based Location Methodology* (Figure 1), developed by Glackin and Adivar (2018). This framework structures the location decision by combining current business model search techniques with underlying lean startup methods and an overall analytical framework for location analysis. We implement the Factor Rating Method (FRM) as a multicriteria decision-making (MCDM) tool which uses multiple location factors and their weights to evaluate alternative locations. AHP is applied to calculate weights for sixteen key factors which emerged from the third iteration of the NVDMV's Business Model Canvas. The AHP method developed by Saaty (1994) helps to determine factor weights by assigning a score to each factor or criteria according to the decision maker's pairwise comparisons with the other factor or criteria.

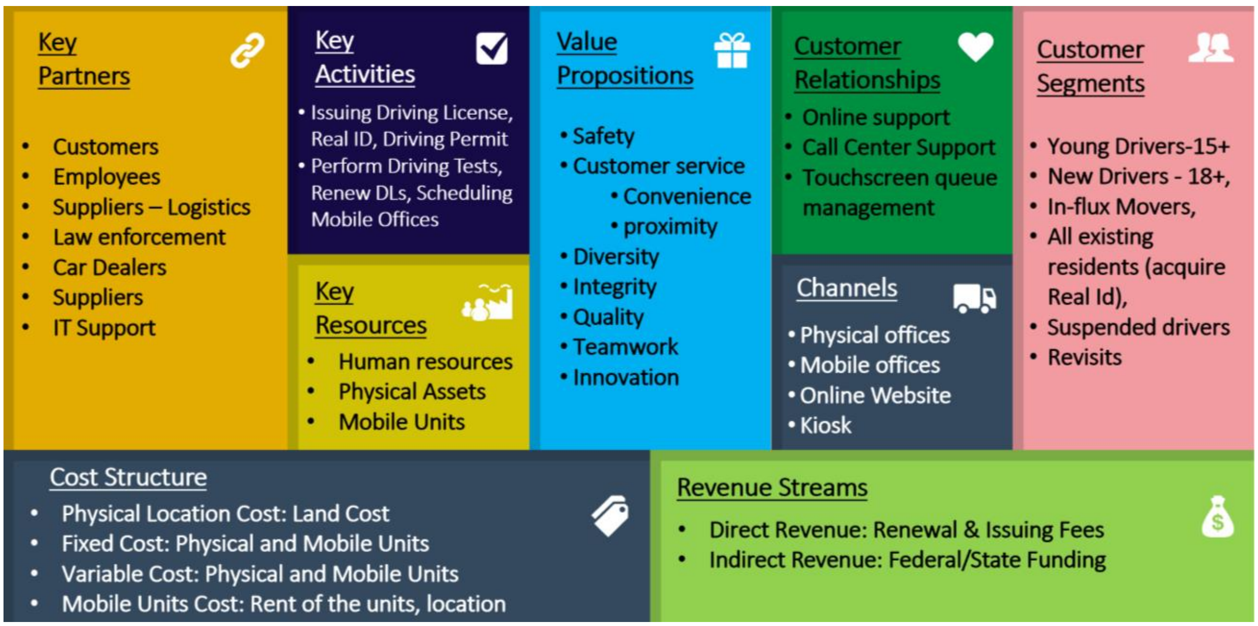


Figure 2. NCDMV's Business Model Canvas

Business Model Framework

Understanding the business model of the NCDMV was critical in determining the correct criteria for the location selection decision. Therefore, the Business Model Canvas for NCDMV was created and iteratively changed over several weeks. The canvas, presented in Figure 2, identifies the key factors involved in creating and capturing value to provide social benefits through contributions of proceeds to the mission-driven activities of the affiliate. The business model canvas suggested population density, cost, sustainability, land availability/ownership flexibility and convenience as important criteria to be considered in the analytical framework.

Analytical Framework

In this section, we present our 7-step algorithm that includes data analytics, analytical hierarchy process and factor rating method.

Step 1. Identification of quantifiable location criteria
Step 2. Using pairwise comparison matrices to calculate AHP weights
Step 3. Determining alternative locations
Step 4. Data mining for scoring
Step 5. Processing and standardizing data
Step 6. Factor rating method to determine total weighted scores
Step 7. Ranking for selecting the best location(s)

SAS 9.4 has been used in Steps 2,5,6 and 7. We used ArcGIS to determine alternative DMV locations based on current and required geographic coverage. Details are presented below.

Step 1. Identification of quantifiable location criteria. NCDMV's Business Model Canvas and literature review suggested using the following location criteria (C1 to C16) to quantify population density, cost, sustainability, land availability/ownership flexibility and convenience.

C1 - Population Density of the County (15+)
C2 - Cost of Living
C3 - Housing Rent (Ave County)
C4 - Housing value
C5 - County Overall Tax Rates (sales)
C6 - All Transit Performance Score - mass transit infrastructure (county)
C7 - Natural Disaster Index
C8 - Unemployment
C9 - Recent Job Growth (over past Year)
C10 -Future Job Growth (Over the next 10 years)
C11 - Clean energy index - Capacity (MW) (County)
C12 - Number of Companies with 500+ Employees (2011)
C13 - Proximity to Shopping Malls
C14 - Proximity to Hospitals
C15 - Proximity to Universities
C16 - Proximity to Highways

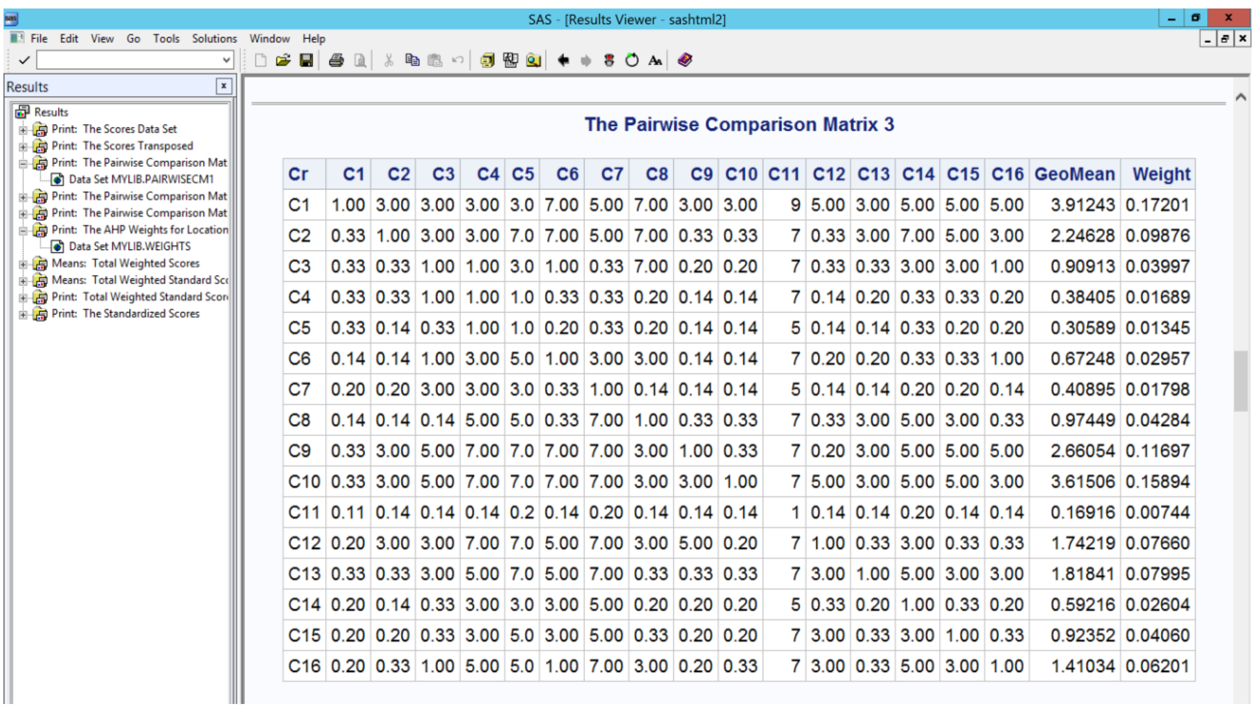
Step 2. *Using pairwise comparison matrices to calculate AHP weights.* After forming a 16x16 square matrix of factors identified in Step 2, we asked experts to make the judgement of the dominance of one factor over another factor based on the following AHP preference scale.

Error! Reference source not found. **AHP Preference Scale**

Intensity of Importance	**Definition**	**Explanation**
1	Equal importance	Two factors contribute equally
3	Moderate importance	Experience and judgment slightly favor one factor over another

5	Strong importance	Experience and judgment strongly favor one factor over another
7	Very strong or demonstrated importance	A factor is favored very strongly over another, its dominance demonstrated in practice.
9	Extreme importance	The evidence favoring one factor over another is of the highest possible order of affirmation.
Reciprocals of above	If factor *i* has one of the above nonzero numbers assigned to it when compared with factor *j*, then *j* has the reciprocal value when compared with *i*	A comparison mandated by choosing the smaller element as the unit to estimate the larger one as a multiple of that unit

An example comparison matrix is shown below. Once all the AHP preference values are assigned for all pairs in the upper diagonal, we calculated the weight of each factor by calculating and normalizing the Geometric Mean. For each expert, we calculated the individual weights using SAS. The finalized weights were considered the average of "weights" of all the individuals.



The Pairwise Comparison Matrix 3

Cr	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	GeoMean	Weight
C1	1.00	3.00	3.00	3.00	3.0	7.00	5.00	7.00	3.00	3.00	9	5.00	3.00	5.00	5.00	5.00	3.91243	0.17201
C2	0.33	1.00	3.00	3.00	7.0	7.00	5.00	7.00	0.33	0.33	7	0.33	3.00	7.00	5.00	3.00	2.24628	0.09876
C3	0.33	0.33	1.00	1.00	3.0	1.00	0.33	7.00	0.20	0.20	7	0.33	0.33	3.00	3.00	1.00	0.90913	0.03997
C4	0.33	0.33	1.00	1.00	1.0	0.33	0.33	0.20	0.14	0.14	7	0.14	0.20	0.33	0.33	0.20	0.38405	0.01689
C5	0.33	0.14	0.33	1.00	1.0	0.20	0.33	0.20	0.14	0.14	5	0.14	0.14	0.33	0.20	0.20	0.30589	0.01345
C6	0.14	0.14	1.00	3.00	5.0	1.00	3.00	3.00	0.14	0.14	7	0.20	0.20	0.33	0.33	1.00	0.67248	0.02957
C7	0.20	0.20	3.00	3.00	3.0	0.33	1.00	0.14	0.14	0.14	5	0.14	0.14	0.20	0.20	0.14	0.40895	0.01798
C8	0.14	0.14	0.14	5.00	5.0	0.33	7.00	1.00	0.33	0.33	7	0.33	3.00	5.00	3.00	0.33	0.97449	0.04284
C9	0.33	3.00	5.00	7.00	7.0	7.00	7.00	3.00	1.00	0.33	7	0.20	3.00	5.00	5.00	5.00	2.66054	0.11697
C10	0.33	3.00	5.00	7.00	7.0	7.00	7.00	3.00	3.00	1.00	7	5.00	3.00	5.00	5.00	3.00	3.61506	0.15894
C11	0.11	0.14	0.14	0.14	0.2	0.14	0.20	0.14	0.14	0.14	1	0.14	0.14	0.20	0.14	0.14	0.16916	0.00744
C12	0.20	3.00	3.00	7.00	7.0	5.00	7.00	3.00	5.00	0.20	7	1.00	0.33	3.00	0.33	0.33	1.74219	0.07660
C13	0.33	0.33	3.00	5.00	7.0	5.00	7.00	0.33	0.33	0.33	7	3.00	1.00	5.00	3.00	3.00	1.81841	0.07995
C14	0.20	0.14	0.33	3.00	3.0	3.00	5.00	0.20	0.20	0.20	5	0.33	0.20	1.00	0.33	0.20	0.59216	0.02604
C15	0.20	0.20	0.33	3.00	5.0	3.00	5.00	0.33	0.20	0.20	7	3.00	0.33	3.00	1.00	0.33	0.92352	0.04060
C16	0.20	0.33	1.00	5.00	5.0	1.00	7.00	3.00	0.20	0.33	7	3.00	0.33	5.00	3.00	1.00	1.41034	0.06201

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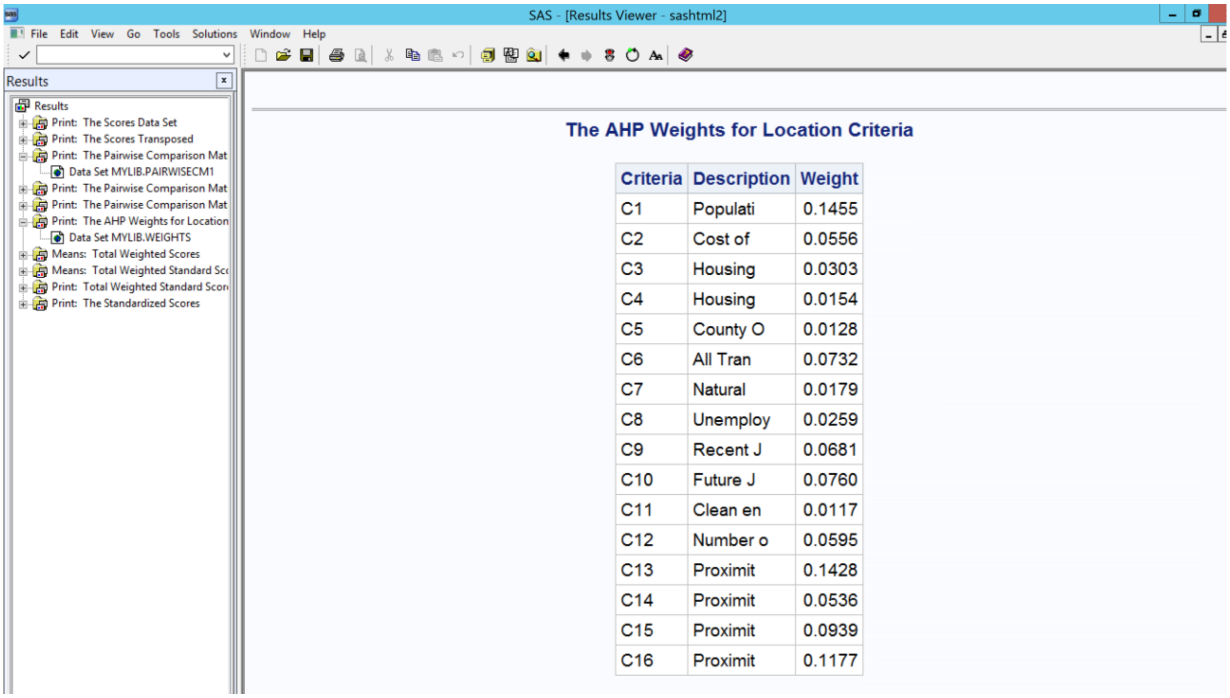
Overall, the most important criteria were found to be C1 – population density (14.55%), C13 – proximity to shopping malls (14.28%) and C16 – proximity to highways (11.77%). The AHP weights that have been used in the remainder of the study are presented below.



Criteria	Description	Weight
C1	Populati	0.1455
C2	Cost of	0.0556
C3	Housing	0.0303
C4	Housing	0.0154
C5	County O	0.0128
C6	All Tran	0.0732
C7	Natural	0.0179
C8	Unemploy	0.0259
C9	Recent J	0.0681
C10	Future J	0.0760
C11	Clean en	0.0117
C12	Number o	0.0595
C13	Proximit	0.1428
C14	Proximit	0.0536
C15	Proximit	0.0939
C16	Proximit	0.1177

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Step 3. Determining alternative locations. Following the weight assessment for all 16 criteria, normalized weights are used for location suitability analysis in ArcGIS. Suitability and service coverage analysis with ArcGIS resulted in full-service coverage with a 20-mile radius around the existing 114 physical and 27 mobile facilities (Figure 3).

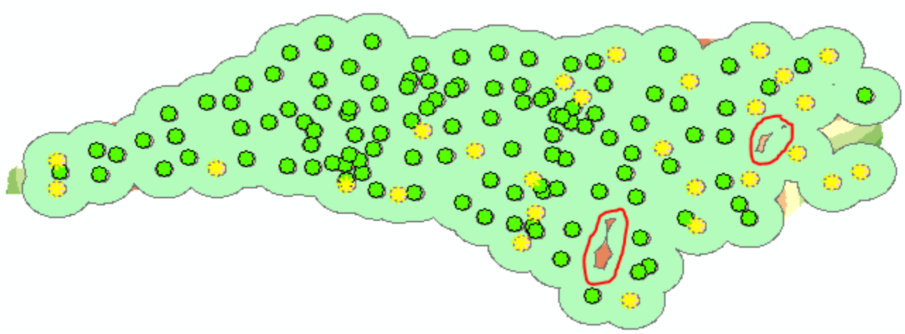

Figure 3. Current coverage with a 20-mile radius

After simulating various radius values for the proximity analysis in ArcGIS, it is observed that the 15-mile proximity offers more convenience and delivers the best results for finding new locations. Based on our projections for the demand and related geospatial data, 18 new alternative DMV locations are determined and visualized through ArcGIS. Figure 4 displays the new alternative locations overlaid with 15-mile-radius service coverage with the existing locations, where “yellow asterisks” represents current mobile locations (27), “blue circle” represents the potential alternate Locations (18).

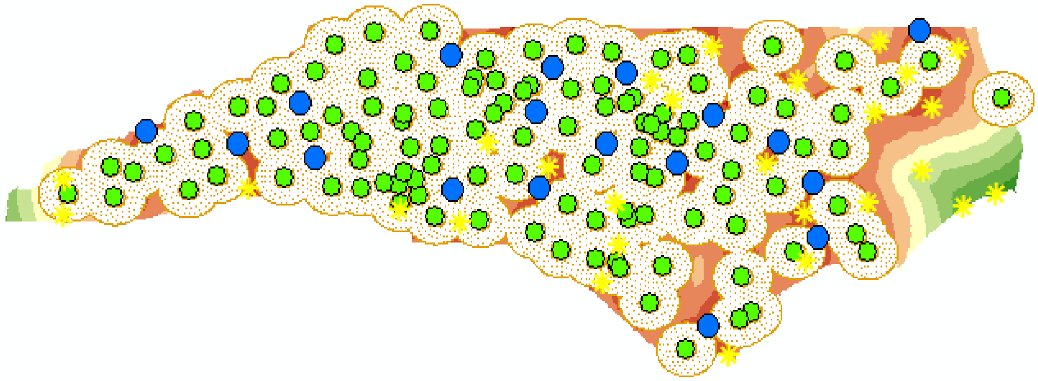

Figure 4. 18 Alternative locations with a 15-mile radius

Step 4. Data mining for scoring. In this step, web search and data collection are used to score each alternative location with respect to sixteen location criteria. The resulting scores are presented below.

SAS - [Results Viewer - sashtml2]

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The Scores Data Set

No	Criteria	Cherokee	BlackMountain	Casar	Collettsville	Pinnacle	Locust	Climax	Moncure	Middlesex	Farmville	Leland	Vanceboro	SouthMills	Maysville	Bahama	JacksonSprings
1	C1	22.00	323.00	171.00	144.00	86.00	126.00	148.00	83.00	142.00	221.00	125.00	118.00	35.00	17.00	858.00	111.00
2	C2	84.60	114.30	80.50	84.10	91.40	87.20	86.80	117.20	87.90	87.70	107.20	87.20	106.00	83.10	102.40	99.50
3	C3	1151.00	1546.00	893.00	905.00	1081.00	1114.00	951.00	1467.00	883.00	1032.00	1311.00	1013.00	1363.00	886.00	1372.00	1080.00
4	C4	145600.00	288600.00	99300.00	108100.00	156900.00	143200.00	136700.00	295800.00	136800.00	121000.00	248300.00	146200.00	252300.00	106200.00	234600.00	225400.00
5	C5	6.80	7.00	6.80	6.80	6.80	6.80	7.00	6.80	6.80	7.00	6.80	6.80	6.80	6.90	7.50	6.80
6	C6	0.00	1.90	0.00	0.00	0.10	0.00	0.20	0.10	1.00	1.30	0.30	0.40	0.00	0.00	4.20	0.10
7	C7	13.00	14.00	16.00	14.00	13.00	15.00	13.00	13.00	14.00	15.00	15.00	16.00	15.00	14.00	16.00	13.00
8	C8	4.40	3.00	4.00	3.80	3.60	3.60	3.70	3.30	5.20	4.30	5.20	4.20	3.80	4.20	3.50	3.90
9	C9	0.80	1.60	1.40	1.60	1.60	1.60	1.30	2.00	-1.10	1.10	2.70	0.40	-0.30	0.00	2.00	2.30
10	C10	35.70	40.90	37.00	37.50	32.40	37.60	31.70	41.80	21.20	32.00	42.80	29.80	29.40	33.50	42.50	40.30
11	C11	305.09	16.97	83.38	26.77	4.23	78.37	23.57	38.59	151.99	30.39	118.88	104.21	5.02	25.26	25.18	33.26
12	C12	24.00	497.00	187.00	132.00	57.00	113.00	208.00	98.00	263.00	333.00	121.00	201.00	4.00	18.00	671.00	179.00
13	C13	0.00	3.00	1.00	1.00	1.00	4.00	5.00	3.00	1.00	1.00	2.00	1.00	0.00	2.00	4.00	0.00
14	C14	4.00	8.00	6.00	8.00	8.00	3.00	5.00	2.00	2.00	2.00	3.00	2.00	2.00	4.00	9.00	5.00
15	C15	0.00	4.00	2.00	1.00	0.00	2.00	1.00	0.00	1.00	2.00	1.00	1.00	0.00	0.00	3.00	1.00
16	C16	4.00	0.00	0.00	0.00	6.00	0.00	4.00	10.00	8.00	7.00	0.00	0.00	0.00	0.00	0.00	6.00

The Scores Transposed

City	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16
Cherokee	22	84.6	1151	145600	6.8	0.0	13	4.4	0.8	35.7	305.09	24	0	4	0	4
BlackMountain	323	114.3	1546	288600	7.0	1.9	14	3.0	1.6	40.9	16.97	497	3	8	4	0
Casar	171	80.5	893	99300	6.8	0.0	16	4.0	1.4	37.0	83.38	187	1	6	2	0
Collettsville	144	84.1	905	108100	6.8	0.0	14	3.8	1.6	37.5	26.77	132	1	8	1	0
Pinnacle	86	91.4	1081	156900	6.8	0.1	13	3.6	1.6	32.4	4.23	57	1	8	0	6
Locust	126	87.2	1114	143200	6.8	0.0	15	3.6	1.6	37.6	78.37	113	4	3	2	0
Climax	148	86.8	951	136700	7.0	0.2	13	3.7	1.3	31.7	23.57	208	5	5	1	4
Moncure	83	117.2	1467	295800	6.8	0.1	13	3.3	2.0	41.8	38.59	98	3	2	0	10
Middlesex	142	87.9	883	136800	6.8	1.0	14	5.2	-1.1	21.2	151.99	263	1	2	1	8
Farmville	221	87.7	1032	121000	7.0	1.3	15	4.3	1.1	32.0	30.39	333	1	2	2	7
Leland	125	107.2	1311	248300	6.8	0.3	15	5.2	2.7	42.8	118.88	121	2	3	1	0
Vanceboro	118	87.2	1013	146200	6.8	0.4	16	4.2	0.4	29.8	104.21	201	1	2	1	0
SouthMills	35	106.0	1363	252300	6.8	0.0	15	3.8	-0.3	29.4	5.02	4	0	2	0	0
Maysville	17	83.1	886	106200	6.9	0.0	14	4.2	0.0	33.5	25.26	18	2	4	0	0
Bahama	858	102.4	1372	234600	7.5	4.2	16	3.5	2.0	42.5	25.18	671	4	9	3	0
JacksonSprings	111	99.5	1080	225400	6.8	0.1	13	3.9	2.3	40.3	33.26	179	0	5	1	6
FourOaks	184	96.7	1201	179500	6.8	0.1	14	3.6	2.9	46.3	189.92	281	1	2	1	6
Gibsonville	651	89.1	1074	150400	6.8	2.7	16	4.1	1.4	32.1	29.23	969	4	4	7	3

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Step 5. Processing and standardizing data. After gathering data from various sources in Step 4 for all the factors or criteria, we standardized it by using

```
PROC STANDARD DATA=mylib.scores_transposed  MEAN=0 STD=1 OUT=mylib.zScores;
RUN;

proc transpose data=mylib.zscores NAME=Criteria
out=mylib.stdScores;
id City;
run;
```

The following display has the part of the standardized data set, which was considered in the next steps.

The Standardized Scores

Criteria	Cherokee	BlackMountain	Casar	Collettsville	Pinnacle	Locust	Climax	Moncure	Middlesex	Farmville	Leland	Vanceboro	Sc
C1	-0.80805	0.57346	-0.12418	-0.24810	-0.51431	-0.33072	-0.22974	-0.52808	-0.25728	0.10531	-0.33531	-0.36743	
C2	-0.84702	1.81504	-1.21451	-0.89184	-0.23752	-0.61398	-0.64983	2.07498	-0.55124	-0.56916	1.17866	-0.61398	
C3	0.10599	2.01390	-1.14018	-1.08222	-0.23211	-0.07272	-0.86003	1.63232	-1.18848	-0.46879	0.87882	-0.56056	
C4	-0.48199	1.75703	-1.20693	-1.06915	-0.30506	-0.51957	-0.62134	1.86976	-0.61978	-0.86716	1.12603	-0.47260	
C5	-0.44856	0.70488	-0.44856	-0.44856	-0.44856	-0.44856	0.70488	-0.44856	-0.44856	0.70488	-0.44856	-0.44856	
C6	-0.59203	1.04082	-0.59203	-0.59203	-0.50609	-0.59203	-0.42015	-0.50609	0.26737	0.52519	-0.33421	-0.24827	
C7	-1.21327	-0.33971	1.40739	-0.33971	-1.21327	0.53384	-1.21327	-1.21327	-0.33971	0.53384	0.53384	1.40739	
C8	0.75501	-1.68425	0.05808	-0.29039	-0.63885	-0.63885	-0.46462	-1.16155	2.14887	0.58078	2.14887	0.40654	
C9	-0.48065	0.29703	0.10261	0.29703	0.29703	0.29703	0.00540	0.68588	-2.32766	-0.18902	1.36636	-0.86950	
C10	-0.01712	0.82650	0.19378	0.27490	-0.55250	0.29112	-0.66607	0.97251	-2.36954	-0.61740	1.13475	-0.97431	
C11	2.96862	-0.69589	0.14876	-0.57124	-0.85792	0.08504	-0.61194	-0.42091	1.02139	-0.52520	0.60027	0.41369	
C12	-0.87703	1.02588	-0.22127	-0.44254	-0.74427	-0.51897	-0.13678	-0.57932	0.08448	0.36610	-0.48679	-0.16495	
C13	-1.20492	0.70878	-0.56702	-0.56702	-0.56702	1.34668	1.98457	0.70878	-0.56702	-0.56702	0.07088	-0.56702	
C14	-0.15855	1.47223	0.65684	1.47223	1.47223	-0.56624	0.24915	-0.97393	-0.97393	-0.97393	-0.56624	-0.97393	
C15	-0.85356	1.42261	0.28452	-0.28452	-0.85356	0.28452	-0.28452	-0.85356	-0.28452	0.28452	-0.28452	-0.28452	
C16	0.29155	-0.87464	-0.87464	-0.87464	0.87464	-0.87464	0.29155	2.04083	1.45774	1.16619	-0.87464	-0.87464	

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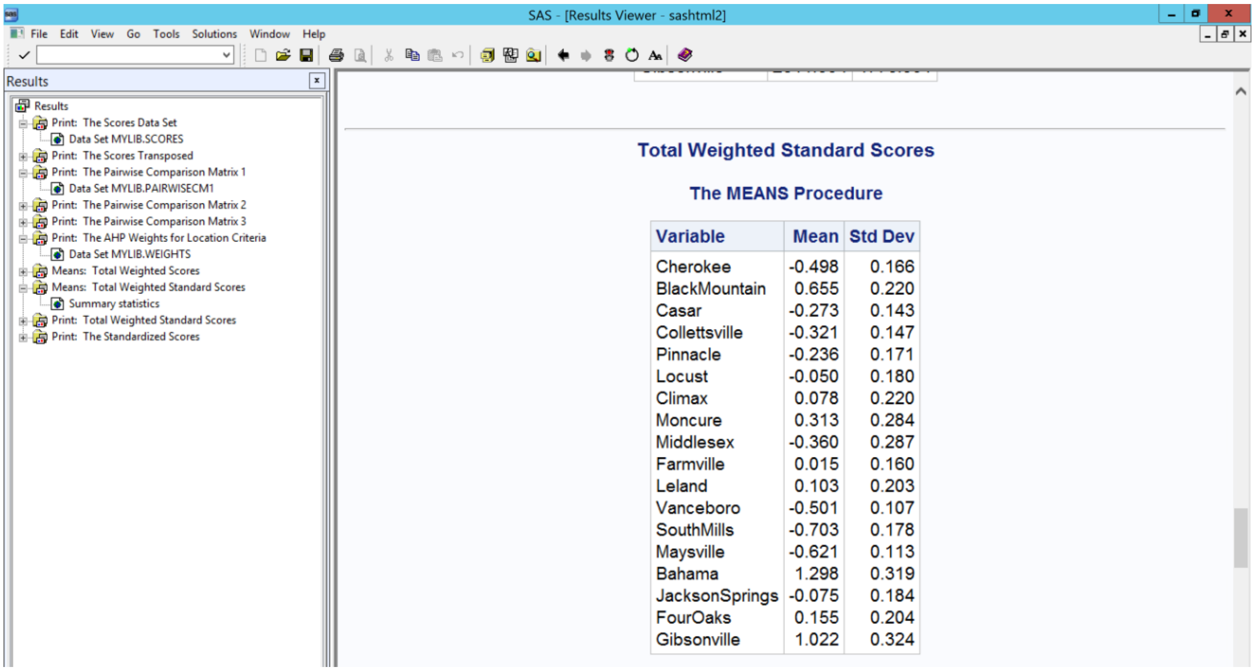
Step 6. Factor rating method to determine total weighted scores

We used the location Factor Rating Method or Multicriteria Decision method which uses multiple criteria, their scores and AHP weights to identify the ranking for the alternative locations. We first merged the weights to the standard scores table and used PROC MEAN to calculate the total weighted score for each of the 18 alternative locations.

```
PROC SQL;
Create table mylib.FactorRating2 as
select * from mylib.stdScores as x, mylib.Weights as y
where x.Criteria=y.Criteria;
quit;

PROC MEANS data=mylib.FactorRating2 maxdec=3 descend mean stddev;
weight weight;
var Cherokee BlackMountain    Casar Collettsville     Pinnacle     Locust
      Climax      Moncure      Middlesex    Farmville    Leland       Vanceboro
      SouthMills  Maysville    Bahama       JacksonSprings     FourOaks
      Gibsonville;
output  out=mylib.FRM ;
title1 'Total Weighted Standard Scores';
run;
```



Total Weighted Standard Scores

The MEANS Procedure

Variable	Mean	Std Dev
Cherokee	-0.498	0.166
BlackMountain	0.655	0.220
Casar	-0.273	0.143
Collettsville	-0.321	0.147
Pinnacle	-0.236	0.171
Locust	-0.050	0.180
Climax	0.078	0.220
Moncure	0.313	0.284
Middlesex	-0.360	0.287
Farmville	0.015	0.160
Leland	0.103	0.203
Vanceboro	-0.501	0.107
SouthMills	-0.703	0.178
Maysville	-0.621	0.113
Bahama	1.298	0.319
JacksonSprings	-0.075	0.184
FourOaks	0.155	0.204
Gibsonville	1.022	0.324

Error! Reference source not found. **Screen Capture for the Total Weighted Standard Scores**.

Step 7. Ranking for selecting the best location(s). We used PROC SORT to rank the alternative locations with respect to their weighted scores.

```
proc sort data=mylib.wlist
out=mylib.finalranking;
by descending MEAN;
run;
Proc print data=mylib.finalranking;
var City Mean;
label Mean='Total Weighted Score'
title 'AHP Ranking for the DMV Locations';
run;
```

Total Weighted Standard Scores

Obs	City	MEAN
1	Bahama	1.29829
2	Gibsonville	1.02227
3	BlackMountain	0.65471
4	Moncure	0.31252
5	FourOaks	0.15537
6	Leland	0.10319
7	Climax	0.07814
8	Farmville	0.01483
9	Locust	-0.05034
10	JacksonSprings	-0.07515
11	Pinnacle	-0.23619
12	Casar	-0.27284
13	Collettsville	-0.32127
14	Middlesex	-0.36021
15	Cherokee	-0.49805
16	Vanceboro	-0.50118
17	Maysville	-0.62140
18	SouthMills	-0.70269

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CONCLUSION

As part of the study, it has been learned that the federal agencies will enforce tougher security standards at airport check-ins, federal buildings, military installations, and nuclear sites at the beginning in 2020. This requirement is posing a challenge against the NCDMV to plan enough locations to handle the increased workload in all parts of the state, including urban and rural areas. This study used several methodologies to find 18 alternative locations to maximize the coverage and to address the current demand & supply. Data-Driven Decision-making techniques have been leveraged to identify new DMV locations to maximize the coverage in the urban and rural area, and the locations have been suggested in the range of 15-20 miles radius from the existing locations. The study utilized the expert knowledge, data mining, Analytic Hierarchy Process (AHP), Geographical Information System (GIS), and SAS Software for selecting DMV locations. SAS PROC MEAN was also utilized to calculate the total weighted score for each of the 18 alternative locations. To continue the study, further optimization models can be used by leveraging SAS optimization procedure (PROC OPTMODEL on SAS Viya) to evaluate the excess or insufficient capacity and to find a count of Mobile vs. Physical alternative locations. Several other important steps may also be taken to increase the awareness and importance of the Real ID conversion to expedite the process and better customer services.

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