Jonah Lehman

ID: 400053918

BIOLOGY 3IR3: INDEPENDENT RESEARCH PROJECT

Landscape Study Using Geological and Land Use Characteristics to Predict Well Water Contamination in The Six Nations of The Grand River

Biology Department, McMaster University, 1280 Main St. W., ON, Canada

Supervisor: Patricia Chow-Fraser

Submitted: December 14, 2020

Abstract

The Six Nations of The Grand River is the largest First Nations reserve in Canada with over 27,000 members, and approximately 12,000 living on the reserve (Indigenous and Northern Affairs Canada, 2020). The Six Nations is located near Brantford, Ontario and many residents face accessibility issues for safe drinking water, with little effort put in by our government to assist them. In this study, we aimed to investigate potential landscape and geological factors that could be related to water contamination of *Escherichia coli* for sampled groundwater wells in 2003, 2004, and 2018, as well as investigate areas of significant clustering through spatial analysis in the Six Nations reserve. We used generalized linear mixed modelling to investigate whether or not potential landscape and geologic predictor variables such as slope, depth, static water level, land coverage, stream proximity and order, and sub-watershed had any significant relationships with the presence or absence of *E.coli* contamination. Although no results show that relationships are occurring with these predictor variables and contamination, spatial autocorrelation analysis and hotspot analysis show that there is a highly significant amount of clustering occurring with wells that are contaminated, particularly at 6th Line and Tuscarora Road. Too few samples exist on record to accurately analyze the effect of landscape and geologic predictor variables on well water contamination. Overall, spatial results indicate potential areas of concern for the community and highlight the need for further research to be conducted within the Six Nations in order to identify threats to drinking water accessibility.

Introduction

Clean, drinkable freshwater is considered an essential human right for all Canadian citizens according to Canada's constitution act of 1982 (Legislative services, 2020). Although Canada has 7% of the world's freshwater resources (ECCC, 2020), not all Canadians have access to this basic human right. Accessibility to potable water in Indigenous communities across Canada is a concerning topic (Lucier et al., 2020), with over 70% of all First Nations communities being under Drinking Water Advisories (DWA) or Boil Water Advisories (BWA; Galway, 2016) between 2003 and 2013. DWAs and BWAs are put in place for communities with drinking water contamination, including harmful substances and organisms such as mercury and *Escherichia coli*. The government of Canada states that drinking water should have no counts of *E.coli* per 100 ml of water, and no more than 0.001 mg of mercury per litre of water (ECCC, 2020). If contaminants such as these are present, a BWA may be advised, meaning that individuals have to boil their water for at least one minute before consuming to prevent potential health risks.

The Six Nations of The Grand River is the largest First Nations reserve in Canada located near the city of Brantford, Ontario, within the Grand River Watershed (Figure 1). With approximately 12,000 community members living on the reserve (Stats Canada, 1996), many residents of the Six Nations have lived with BWA's on and off for many years due to inaccessibility of clean drinking water caused by well water contamination (Burnside, 2005; Lucier et al., 2020). Even though accessibility to clean drinking water is a human right, the Canadian government has provided little effort to assist this community. Fresh water stations have recently been implemented such that community members may fill up on water for use in their homes, however, this does not fix the issue of contamination in community member's wells within the reserve (Burnside, 2005).

There is little understanding as to what factors may be contributing to well water contamination within the Six Nations. Contamination of groundwater in wells may occur through various environmental factors, and in this study, we aimed to analyze previously sampled well data taken within the Six Nations of The Grand River in 2003, 2004, and 2018 to investigate if surface and subsurface properties are significant predictors of well water contamination. Landscape factors such as land cover, soil substrate type, slope, and stream proximity and order are important surface features that we predicted to have a potential effect on well contamination. Subsurface properties were also predicted to have an effect, as well contamination may also be influenced by geologic factors such as depth to bedrock, static water level, and elevation (ECCC, 2019). It is important to investigate all of these potential predictors of contamination, as well as spatially analyze instances of well contamination, as results of this study could inform the Six Nations community of any underlying factors or locations that may threaten the safety of their drinking water.

Methods

Concept Map

A concept map of methods was created for this investigation, and methods were split up into two parts (Figure 5). The first part involved the use, processing, and formatting of various datasets, where the second part made use of various forms of spatial and non-spatial analyses to understand regions of interest, as well as what geological and surficial predictor variables may be affecting contaminated wells.

Data

We utilized multiple sources of data in this project, with the main sets of sampled well data from 2003, 2004 (Burnside, 2005), and 2018 (Global water futures, unpublished data). These datasets (Table 1) are shapefiles containing locations of sampled wells, cisterns, and faucets that were tested for multiple contaminants including *E. coli*, total coliforms, and mercury. The 2003/2004 dataset (Figure 2) has information on *E. coli*, location, decade drilled, type of well, and estimated depth, with 119 wells sampled in 2004 and 57 wells sampled in 2003. The 2018 dataset (Figure 3) contains the same information along with additional well and survey information such as estimated age, ownership, and physical-chemical parameters measured on-site. It should also be noted that 2018 was the only year that mercury was sampled, with 48 samples taken. Due to the lack of sufficient mercury samples for analysis, this study focuses on *E.coli* contamination. Since both geological and surficial properties were investigated in this project (Figure 4), additional data was accessed and used alongside the surveyed well data from 2003, 2004, and 2018. It was decided that two shapefiles would be developed in this project, one layer for geological (subsurface) properties (Table 2), and one for landscape (surficial) properties (Table 3).

The subsurface shapefile was composed of information obtained from overlapping historical well records (Table 1) found in the Water Well Information Systems Database (WWIS; Ministry of Environment, Conservation & Parks, 2019), which included information on static water level, depth to bedrock, depth of well, date drilled, elevation, and slope (Table 3). This is an important database, as it has records of all legally constructed wells that were bored or drilled by contractors and drilling companies between the 1940s and the early 2000s for the Six Nations reserve. All of the hydrogeological features that are in each historical record are important properties to consider as potential predictors of *E.coli* contamination. Due to the inaccurate nature of historical WWIS records, the subsurface shapefile is a subset of all sampled wells since only accurately overlapping information was included for analysis. Elevation and slope are two equally important factors that can help identify the direction of water flow both below and above the surface, which helps to identify any unusual patterns caused by potential contaminants in water sources. Well depth must also be accounted for, since it is generally considered that the deeper the well, the safer it is for drinking. This is because contaminants leaching from the surface become more filtered out as depth increases (ECCC, 2019). This means that patterns of shallower well depths may give us an understanding as to how much effort was put into drilling the well, and patterns in contamination at specific depths. Static water level, on the other hand, generally identifies where the water table is for wells that are in unconfined aquifers (ECCC, 2019). This ties perfectly into the last important property investigated, which is the depth to bedrock. This property can tell us whether or not the well reached bedrock, which can then be used to assume whether or not a confined aquifer is being used for each well. The safest drinkable water sources are from confined aquifers that break through impermeable bedrock, as this impermeable layer protects confined water sources from the introduction of contaminants (ECCC, 2020). Unconfined aquifers may contain drinkable water, however they are more at risk of becoming contaminated, as they are fed by water that can come from runoff or subsurface flow that may contain contaminants (ECCC, 2019).

There are multiple potential predictors that we thought may be linked to contamination from the surface that was included in the surface shapefile. The first predictor variable we investigated was watercourse. We were interested in stream order and proximity because we noticed that some wells that were contaminated were close to streams. Another layer of interest is the sub-watershed that each well lies within. There are three different sub-watersheds that go through the Six Nations, and different paths of water may bring in different contaminants into wells. It is also important to identify if different watersheds have different proportions of contamination, as this can give insight as to what watersheds may be bringing in contaminants. The Grand River Conservation Authority (MacVeigh, Zammit & Ivey, 2016) has stated that the Six Nations reserve is made up primarily of clay plains with low permeability (MacVeigh, Zammit & Ivey, 2016). When precipitation occurs, the impermeable clay substrate leads to less areas of infiltration and more surface runoff into land, culverts, streams, and rivers. Runoff may be reduced in forested areas, and exacerbated in urban and agricultural areas (MacVeigh, Zammit & Ivey, 2016). Furthermore, Ontario government states that regardless of the source, farming areas may be much more susceptible to ground water contamination if contaminants enter the ground (ECCC, 2019). Considering the Six Nations has a large amount of agricultural land cover, these factors are important to account for, as wells could be acquiring more runoff in some regions of the Six Nations compared to others.

GIS & Data Processing

A detailed flow chart was created to show the process used in ESRI® ArcGIS Pro to develop and format the surface and subsurface shapefiles (Figure 6). Firstly, the 2003 and 2004 datasets had to be separated from each other in order to create two shapefiles with wells surveyed from each year. This allowed for the 119 samples in 2004 to be separate from the 57 samples from 2003. Next, the shapefiles from these years were joined with the 2018 data to get one shapefile with sampled data from all years. This newly created shapefile with 310 entries was then copied, such that it may be used as the basis of both the surface and subsurface shapefiles that will be analyzed and created.

The subsurface shapefile was made from a copy of sampled wells from all years by identifying overlapping wells from the WWIS layer that have historical well information. By putting a 100m buffer around each well from historical records, the intersect tool was used to identify potential historical wells that are the same as sampled wells from 2003, 2004, and 2018. This was performed because the WWIS layer with historical well data has low spatial accuracy, as locations were based off of drawings of well locations made between the 1940s to early 2000s. By using 100m buffers and the intersect tool, we can potentially identify which historical wells were sampled. Those that overlap within 100m may be considered to be the same well and have the historical information spatially joined to the overlapping wells. If multiple records or surveyed wells lie within the buffer region, dates between surveyed wells and WWIS records were manually compared to identify if a match occurred. If a match could not be proven through manual identification, overlapping sampled wells were omitted from the new shapefile. This created a subset of surveyed wells that had geologic and Z-axis information. One final step was performed, where the 'Summarize Z Data' tool was used in ArcGIS Pro to incorporate the mean elevation and slope in a 10m area around each well using a LiDAR derived DTM provided by the Ontario Ministry of Natural Resources and Forestry (OMNRF, 2020).

The surface shapefile was created using a copy of the all sampled years shapefile to incorporate multiple different watershed and landscape properties of each well into the result. Firstly, the Nearby tool was used in ArcGIS Pro with the Ontario Hydrocourse Network (OHN; OMNRF, 2010) to summarize the distance (in meters) from each well to the closest stream, river, creek, or culvert. The Join tool was then used to join the Strahler order of the closest watercourse to each well. This resulted in two new columns that identify the closest watercourse and their Strahler order for each sampled well. Next, a spatial join was used between the surveyed well shapefile and a sub-watershed polygon supplied by the GRCA (MacVeigh, Zammit & Ivey, 2016), summarizing each Subwatershed within the Six Nations that each well lies within. This created a column that lists each sampled well as “McKenzie Creek”, “Boston Creek”, or “Lower Grand River” watershed. To incorporate land use information around each well, a 10m buffer was created around the sampled wells shapefile and the Summarize Within By Majority tool was used to summarize land usage in a 10m area around each well based on the Southern Ontario Land Resource Information System (SOLRIS) 3.0 (SOLRIS 3.0; OMNRF, 2019). SOLRIS 3.0 uses the OMNRF's Ecological Land Classification for southern Ontario based off of land coverage classification by Lee et al, (1998). Land coverage types were grouped into “Agricultural”, “Forest”, “Urban/Road” land coverage types, which were incorporated into a final column in the new surface shapefile with the most common land use type in a 10m radius for each surveyed well.

Analysis Using Generalized Linear Mixed Models and Contingency Tables

We used the statistical program JMP® SAS to format the surface and subsurface shapefiles, as well as conduct non-spatial analysis. Firstly, each shapefile was translated into a spreadsheet format, and a column was created to identify wells with presence and absence of a contamination. Based on *E.coli* concentrations, any sampled wells with concentrations that were greater or equal to 1 were considered contaminated and marked as “Y” in the new column. Those that had concentrations of 0 when sampled were marked as “N” in the new column. A well ID column was also created for wells that are the same, such as the 57 wells in 2003 that were sampled once again in 2004. This is an important step for generalized linear mixed modelling, as resampled wells can create random variation and need to be accounted for.

Generalized Linear Mixed Modelling of the surface and subsurface data occurred through a JMP add-in (Dong, 2020), with properties from Table 2 and Table 3 used as predictor variables, and presence/absence of contamination as the response variable. This method was used over other types of linear regression, as resampled wells are an area of random variability, and can be accounted for by this method. Furthermore, this method was used because it allows for both numerical and categorical predictor variables, both of which were included in this investigation. We used the Well ID column as the random variable for both analyses of the surface and subsurface data and used scatterplot matrices to compare predictor variables to each other to ensure there were no patterns or correlations between predictors before executing the analysis. If any predictor variables were correlated with each other, one of the correlated predictors were excluded from the analysis.

Contingency tables were also performed in JMP SAS using the Fit Y by X tool. Contingency tables were used to look at differences in presence and absence of contamination for two potential predictor variables; "Decade Drilled" and "Road". These two predictors were reformatted to be grouped into an "other" category if there were less than five observations for each road name or decade. A Chi Square analysis was then performed with each contingency table to test differences between proportions of contaminated and uncontaminated wells for all roads in the Six Nations, and the decade that wells were drilled. It should be noted that "Decade Drilled" is from the subsurface shapefile, where "Road" is from the surface shapefile. This means that there are much fewer observations for analysis of Decade Drilled compared to road.

Spatial Autocorrelation and Hotspot Analysis

Spatial analysis was performed for the surface shapefile (Figure 8) to investigate if spatial autocorrelation and clustering are occurring for surveyed wells based on presence and absence of

E.coli contamination. Firstly, we used the Global Moran's I tool in ArcGIS pro to look at dispersion or clustering of contaminated and uncontaminated wells. Moran's I analysis looks at location of datapoints and tries to evaluate if datapoints of similar type (such as contaminated or uncontaminated) are more or less closely related to each other by distance. Moran's I evaluates whether the pattern expressed is clustered, dispersed, or random. We used this tool to investigate if the distribution of contaminated and uncontaminated wells (Figure 8) shows significant clustering. If significance is detected, this suggests that a pattern of contamination is occurring within the Six Nations that is not due to chance.

Getis-Ord Gi* was the second spatial analysis performed with the surface dataset. Also known as the Optimized Hot Spot Analysis tool in ArcGIS Pro, this analysis is similar to spatial autocorrelation, but instead creates a series of polygons that identify areas with high densities of incident data (such as presence of contamination). This tool also assesses significance of incident density for areas with 95-99% confidence. The output returns multiple polygons in a fishnet or hexagonal grid pattern that make up the area of interest (Six Nations Boundary), and categorizes them as significant hotspots (densely contaminated), or significant cold spots (uncontaminated). We used this analysis with a 2km hexagonal grid pattern, rather than the square grid to reduce sampling bias of points and ensure that each grid had at least one observation. This analysis was chosen as the result may help identify environmental factors that could influence contamination within grids of significant clustering.

Results

Generalized Linear Mixed Models & Chi Square Analysis

Results from generalized linear mixed modelling found no significant results for both surface and subsurface shapefiles (Figure 9). Similarly, Chi square analysis through contingency tables did not find any significant results either for both Roads or Decade Drilled (Table 4). Bar graphs were created to display differences between contaminated and uncontaminated proportions of wells for both decade drilled and roads (Figures 10 & 11). Figure 10 shows all decades had more uncontaminated wells than contaminated, except for the 50s with no uncontaminated wells sampled, and only one contaminated well. From 1970s to 1990s, contamination seems to increase, until the 2000s. Figure 11 shows the 13 most surveyed roads, where the remaining roads with less than 5 observations were grouped into "other". All roads had more uncontaminated wells than contaminated, other than Tuscarora road with 11 contaminated wells. Both Tuscarora and 6th line interestingly seemed to have the highest number of contaminated wells.

Spatial Autocorrelation and Hotspot Analysis

Spatial autocorrelation results gave a Moran's I value of 0.5687, a Z-score of 6.75, and a significant P value that was less than 0.001. The results showed that out of all sampled wells, there is a significant level of clustering occurring between contaminated and uncontaminated wells. Hot spot analysis highlighted an ~11km^2 area within the reserve that had significant hotspots of contaminated wells with a 99% confidence level (Figure 12). All contaminated and uncontaminated points were further mapped out in this significant region of contaminated clustering, which seemed to occur around the intersection of Tuscarora Road and 6th Line (Figure 13).

Discussion

For the generalized linear mixed models, no results were significant, meaning that none of the potential predictor variables are proven to be good estimators of *E.coli* contamination. Starting with the Subsurface shapefile, not all predictor variables could be compared due to correlations with each other. Elevation and slope were heavily correlated to each other, meaning one had to be excluded (in this case, elevation). Depth and static water level were also heavily correlated to each other, meaning that one had to be excluded (static water level). There were other strange patterns in predictor variable data that may be related to the insignificant results found. For example, Strahler order needed to be grouped due to lack of observations for stream orders greater than 3. Because of this, Strahler order was grouped as 1, 2, and greater than or equal to 3. Land coverage is another good example, as most wells were in areas of agriculture or urban/road coverage which left very few observations with forested land coverage. Based on these patterns, it is likely that a larger sample size is needed to accurately identify if any of these predictors have an effect on well contamination.

Moran's I results indicate that that the spatial distribution of contaminated and un-contaminated wells in the dataset are more spatially clustered than would be expected if underlying spatial processes were random (less than 1% likelihood). This means there is some external factor that is likely influencing well contamination. Hotspot analysis reveals an area of significant contamination clustering in the hexagonal grid with 99% confidence (Figure 12), located around the intersection of Tuscarora road and 6th line. This highly significant hotspot suggests that there may be an environmental factor near that is influencing contamination in this area, which agrees with results seen in figure 11. Both figure 11, as well as Table 4 show that Tuscarora road and 6th line have the highest contamination counts compared to other roads, which further supports our predictions that this area is key to understanding what may be influencing well contamination.

We decided to further investigate environmental variables in the significant hotspot that may be related to occurrences of contamination (Figure 14). Although depth was already analyzed through generalized linear mixed modelling, it is important to note that most wells within the Six Nations are very shallow. The shallowest well is less than 5m deep, where the deepest is ~30m. We investigated well depth via visual analysis (Figure 14) and noticed that within the area of clustering, many wells that were less than 15 meters deep seemed to be contaminated. Unfortunately, the sample size in this dataset is too small to definitively prove if depth may influence contamination, and furthermore there are still contaminations occurring in wells that are up to 30 meters deep. Depth may be an area for future research to focus on, as a higher sample size may be able to shed light on specific depths that contamination occur at.

Another environmental variable further looked at was watercourse. It was noticed that both the Grand River and McKenzie creek run through the significant hotspots (Figure 15), and furthermore, the wastewater lagoon runs very close to McKenzie Creek a few km upstream on this region. There are not enough sampled wells in this area to suggest that either of these may be a point source, however the regions of the Grand River and McKenzie creek that run through the hotspot may be key for identifying contamination in future research.

Conclusion

In summary, this study investigated potential effects of landscape and geological features on the presence and absence of *E.coli* contamination in sampled wells within the Six Nations, as well as spatial autocorrelation and clustering of contamination. We found that no predictor variables were found to influence presence-absence of well water *E. coli* contamination due to the small sample size, however we identified that significant clustering of contaminated wells is occurring around the intersection of Tuscarora Rd and 6th Line. We suggest future research focus on sampling more wells within the reserve to gather more information on date, depth, and whether or not bedrock was reached, as well as investigate stretches of the Grand River and

McKenzie Creek that run through the significant hotspot. These factors may help to reveal potential environmental variables that could have an effect on contamination, and these future results could inform the Six Nations community of any underlying factors that may threaten the safety of their drinking water.

Acknowledgements

We wish to thank Sawsan Makhdoom, Nick Luymes, Pat Chow-Fraser, and others from the Chow-Fraser lab for offering, data, support, and advice in this project. We thank Neegan Burnside Engineering and Environmental Ltd. and the Global Water Futures Ecosystem Health Sub-team for offering sampled well data. Special thank you to the Six Nations of the Grand River for allowing us to work on this project.

Table 1: Primary well data used for analysis.

DATASET	DETAILS	SOURCE
2003/2004 Dataset	Sampled wells for *E. coli* and total coliform, includes location data, date drilled, cistern or well, and depth in meters. 119 Records in total, 57 from 2003	Neegan Burnside Engineering and Environmental Ltd. Hydrogeological study (2005)
2018 Dataset	132 samples of *E.coli* contamination, address, type of well, location, owner, and other physical-chemical data. 48 of these samples looked for mercury contamination.	Global Water Futures Ecosystem Health Sub-team (2018; unpublished data)
Water Well Information Systems (WWIS) Database	Historical well records shapefile with geological and well information, date drilled, and Z-axis information such as depth, depth to bedrock, static water level, whether bedrock was reached or not. Older well records have inaccurate coordinates with locations based off of drawings.	WWIS - Ministry of Environment, Conservation & Parks (2019)

Table 2: Geospatial data used to create subsurface shapefile.

CHARACTERISTIC (PREDICTOR VARIABLE)	**DESCRIPTION**	**SOURCE**
Depth	Depth of well from surface in meters.	Well Water Information System Database (WWIS) - Environment and Energy Ontario
Static Water Level	Height of water from base of well (m) when not pumping, Approximate depth of water table in unconfined aquifer.	WWIS - Environment and Energy Ontario
Depth to Bedrock	Depth (m) from ground surface to bedrock (top of confined aquifer). If values are 0, bedrock was not reached and the well uses water from unconfined aquifer.	WWIS - Environment and Energy Ontario
Was Bedrock Reached?	Yes (Y) or No (N) as to whether well was dug below bedrock.	Derived from WWIS - Environment and Energy Ontario
Date Drilled	Day/Month/Year that well was finished. Values range from 1950s-2000s.	WWIS - Environment and Energy Ontario
Elevation	Mean elevation (m.a.s.l) in a 10m area around each well.	LiDAR Derived Digital Terrain Model (DTM) - Ontario Ministry of Natural Resources and Forestry (OMNRF)
Slope	Mean slope in a 10m area around each well.	Derived from LiDAR DTM using ArcGIS Pro - OMNRF

Table 3: Geospatial data used to create surface shapefile.

CHARACTERISTIC (PREDICTOR VARIABLE)	**DESCRIPTION**	**SOURCE**
Stream Order (Strahler)	Strahler order of closest stream, river, culvert, etc. Grouped into orders 1, 2, or ≥ 3.	Ontario Hydro Network (OHN) Database - OMNRF
Proximity to Closest Stream	Distance in meters to closest stream, river, or culvert.	Derived from (OHN) Watercourse – OMNRF Using ArcGIS Pro
Land Coverage	Primary land coverage in 10m area around well. Land coverage types are grouped into "Forest", "Agriculture", "Urban/Road".	Southern Ontario Land Resource Information System (SOLRIS) Version 3.0 - OMNRF
Subwatershed	Subwatershed that well lies within. Grouped as McKenzie Creek, Boston Creek, and Lower Grand River Subwatersheds.	Grand River Conservation Authority (GCRA)
Road Name	Name of road that the property is on for each sampled well.	Derived from sampled well data of all years (2003, 2004, 2018).

Table 4: Proportion of Contaminated and Uncontaminated Wells by Road.

Count % Total X^2 Value	Contaminated	Uncontaminated	Total
1st Line	14 4.52 0.0104	6 1.94 0.0267	20 6.45
2nd Line	20 6.45 0.0356	9 2.90 0.0911	29 9.35
3rd Line	23 7.42 0.4055	5 1.61 1.0395	28 9.03
4th Line	21 6.77 0.0156	9 2.90 0.0400	30 9.68
5th Line	16 5.16 0.397	3 0.97 1.02	19 6.13
6th Line	27 8.7 0.004	11 3.54 0.010	38 12
Cayuga Road	13 4.19 0.133	7 2.25 0.34	20 6.44
Chiefswood Road	19 6.1 1.003	2 0.64 2.57	21 6.75
Mohawk Road	7 2.25 0.005	3 0.967 0.013	10 3.2
Onondaga Road	14 4.51 0.39	9 2.90 1.00	23 7.4
Other	7 2.25 0.042	2 0.645 0.109	9 2.9
River Range Road	15 4.8 0.00075	6 1.9 0.0019	21 6.7
Seneca Road	11 3.5 0.086	3 0.96 0.219	14 4.5
Town Line	9	1	10

	2.90 0.45	0.322 1.16	3.22
Tuscarora Road	7 2.25 2.73	11 3.54 7.00	14 5.8
Total	223 71.94	87 28.06	310 100
Prob>ChiSq	0.1141		

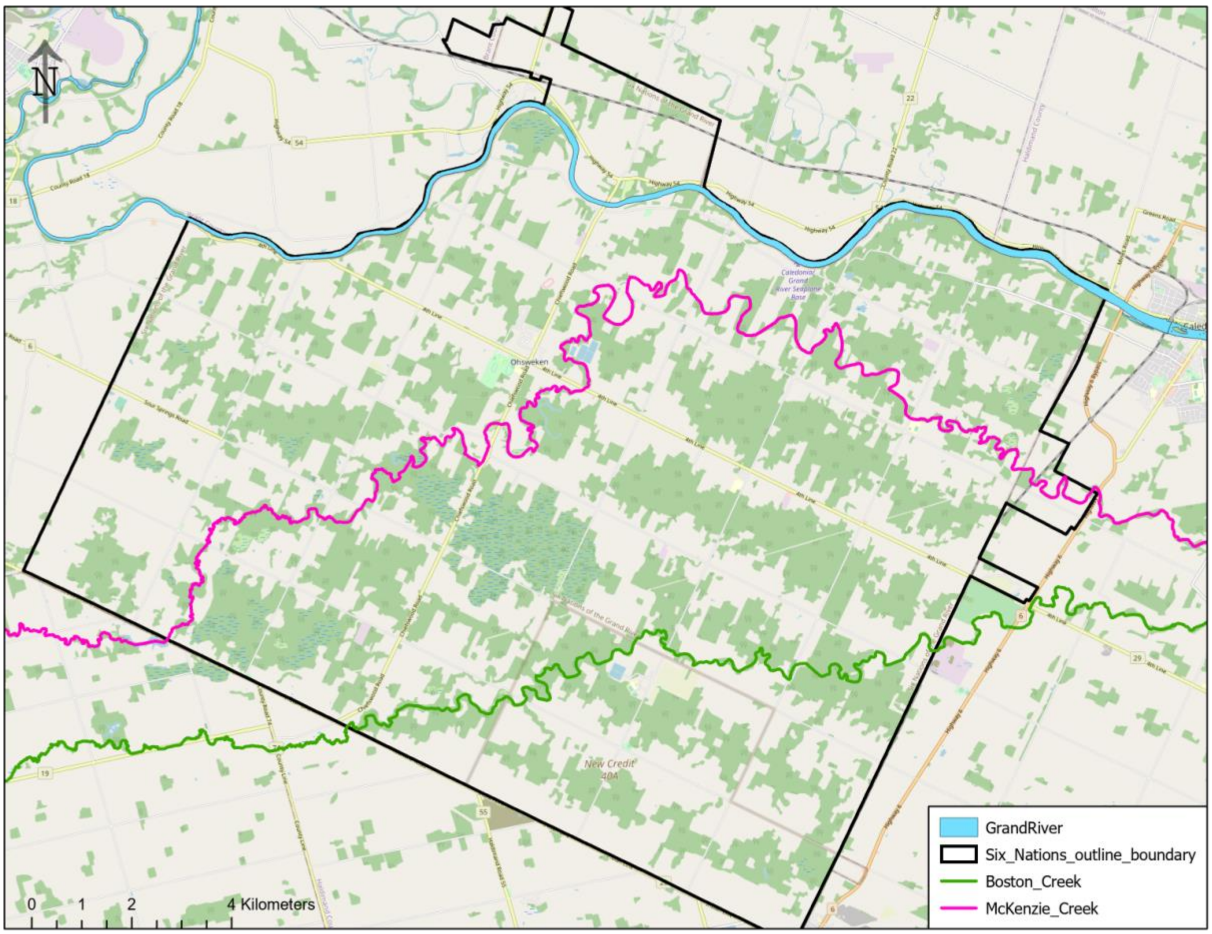


Figure 1. Six Nations of The Grand River First Nations Reserve, located in Southern Ontario.

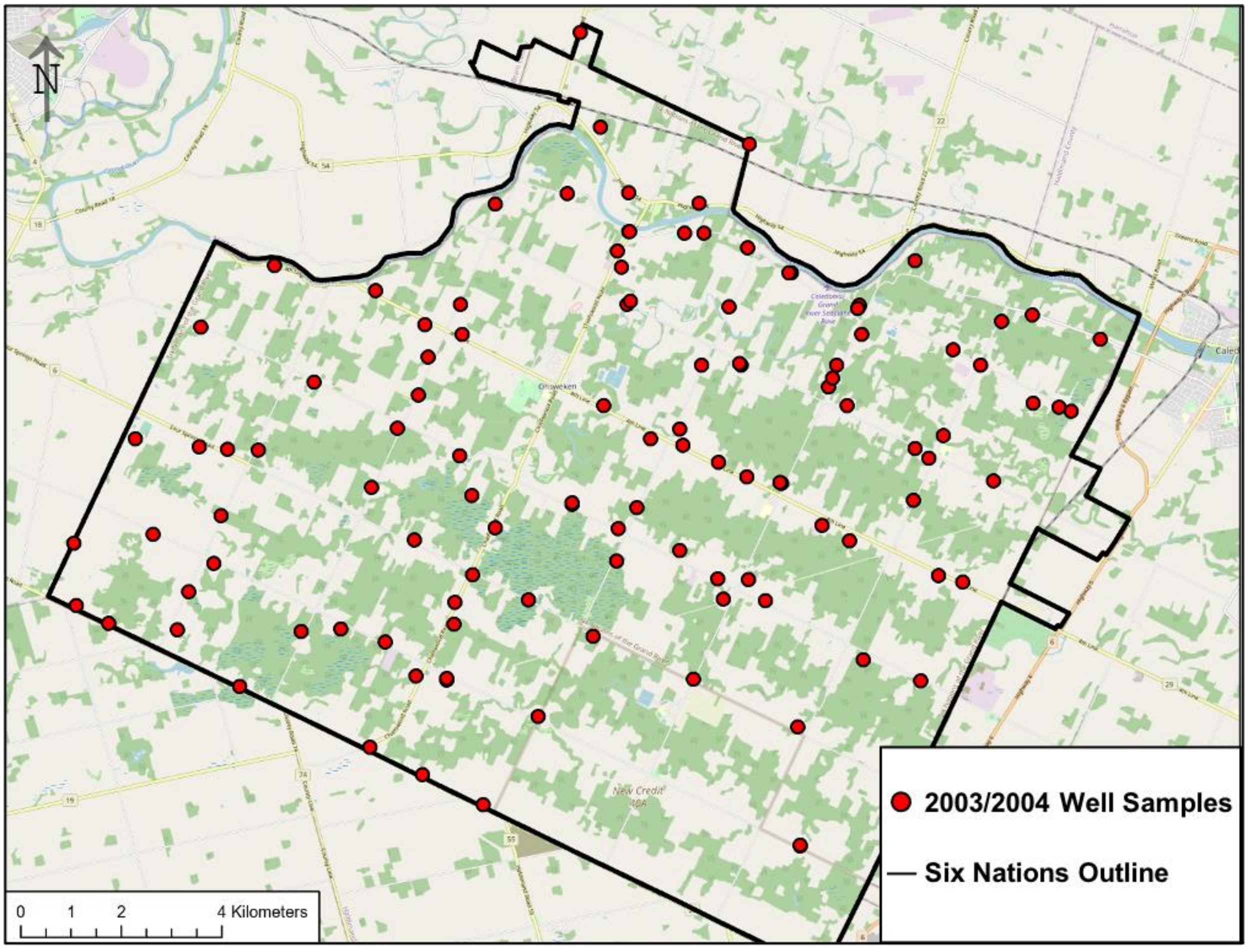


Figure 2. Sampled well locations for *E.coli* contamination in 2003 and 2004. Dataset from Neegan Burnside Engineering and Environmental Ltd. Hydrogeological study (Burnside, 2005)

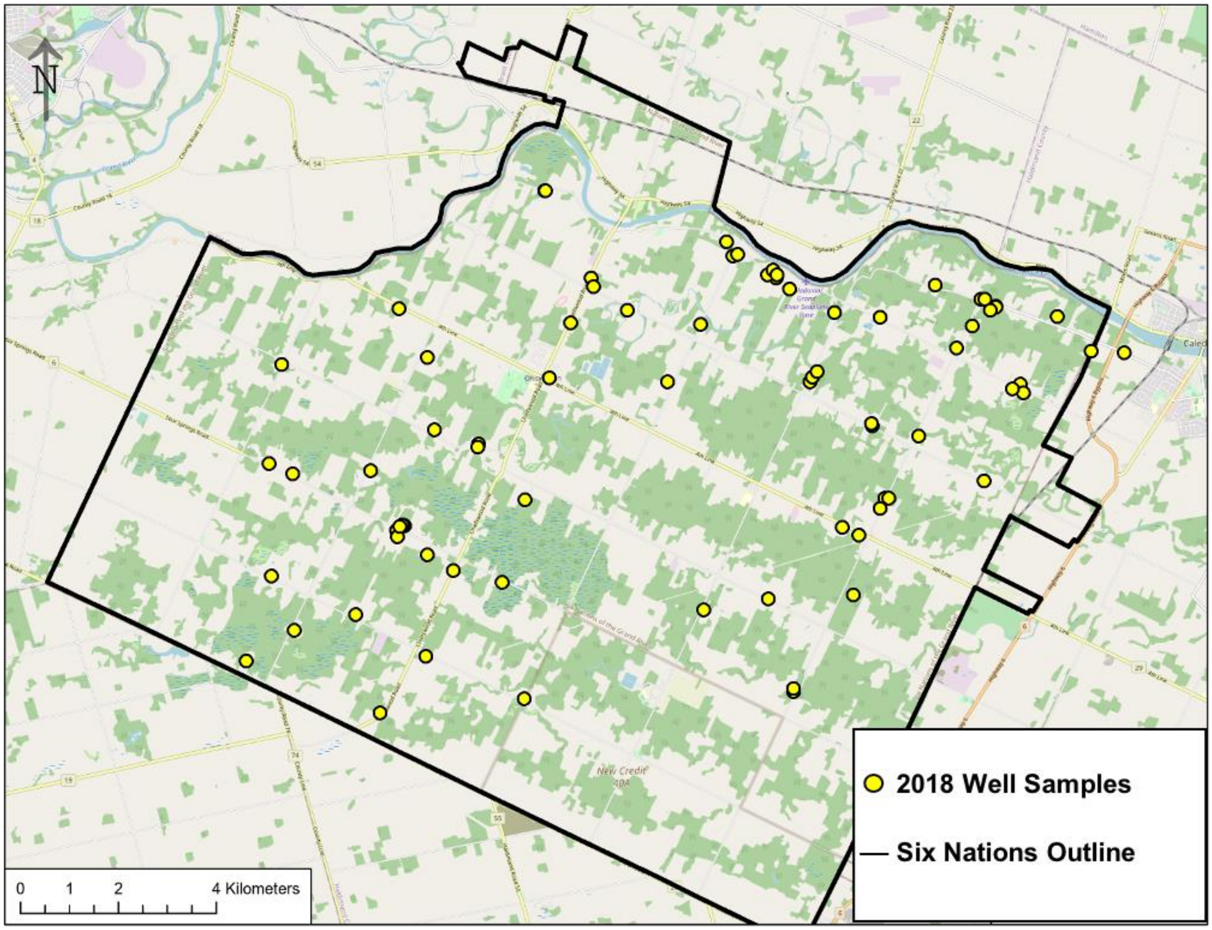


Figure 3: Sampled well locations by Global Water Futures Ecosystem Health Sub-team in 2018. (Makhdoom et al., 2018)

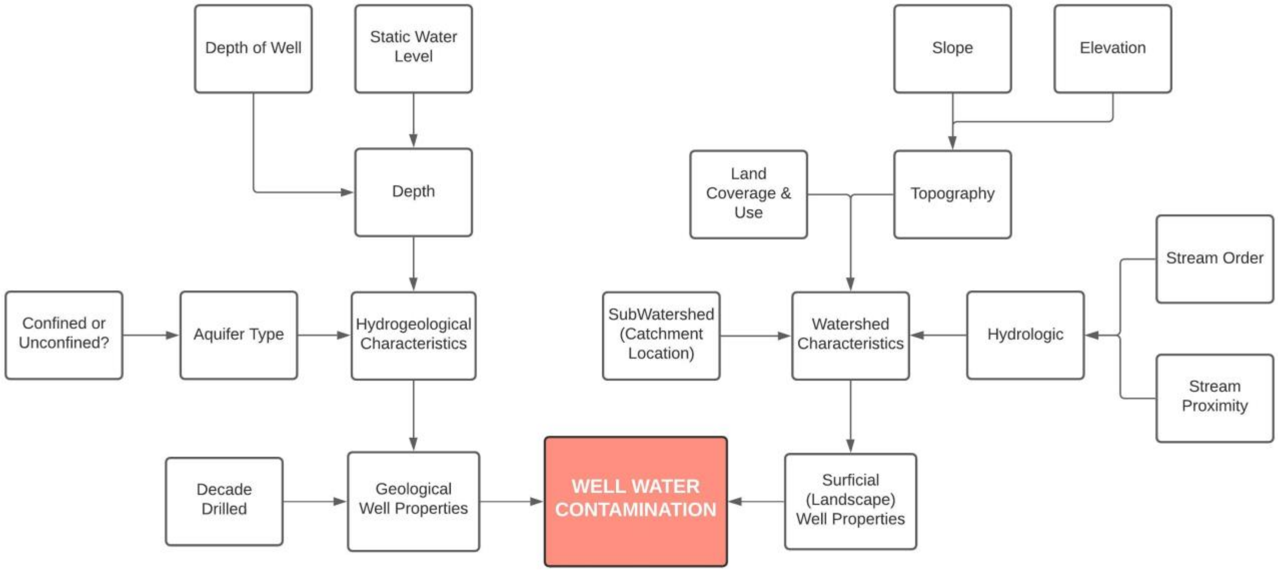


Figure 4: Concept map of potential environmental factors that may lead to well water contamination. Well contamination is split into two properties, (1) geological (subsurface) properties, and (2) surficial (landscape) properties.

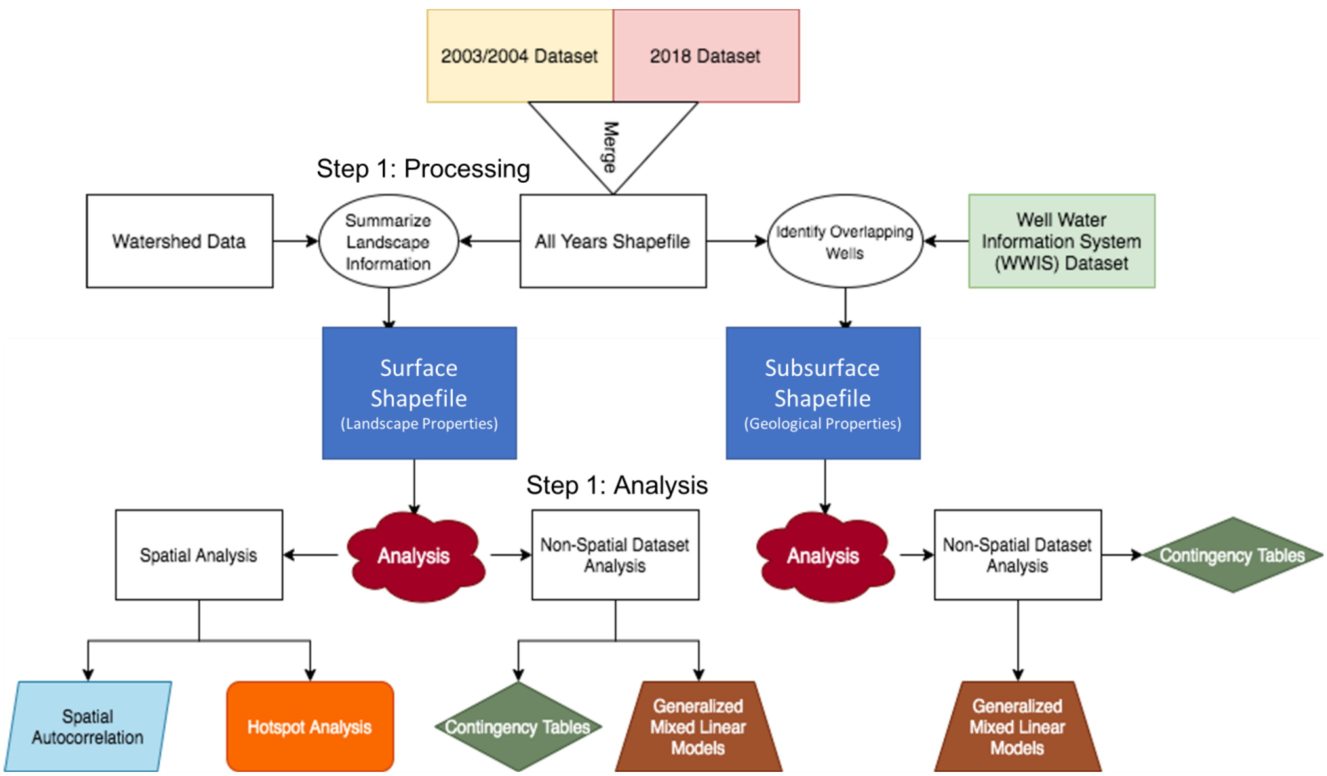


Figure 5: Flow chart of methods used to investigate environmental predictors and presence of *E.coli* contamination in wells. Part (1) involves the creation of two separate shapefiles (surface properties, and subsurface properties), and Part (2) involves the spatial and non-spatial analysis. Generalized linear mixed models and contingency tables were used for non-spatial analyses of both shapefiles, where spatial analysis was used for only the subsurface shapefile.

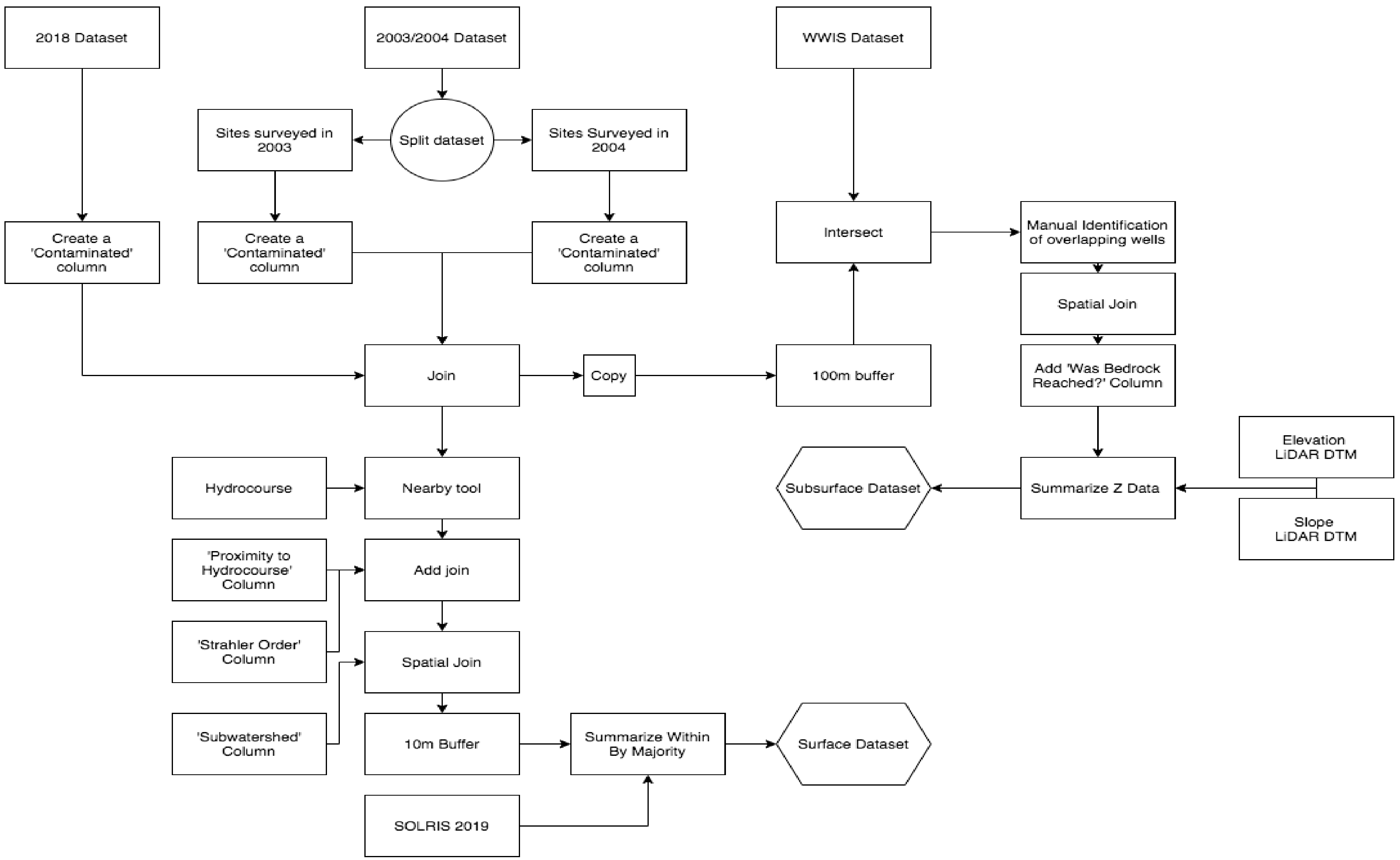


Figure 6: GIS processing methods used to create surface and subsurface shapefiles used in analysis.

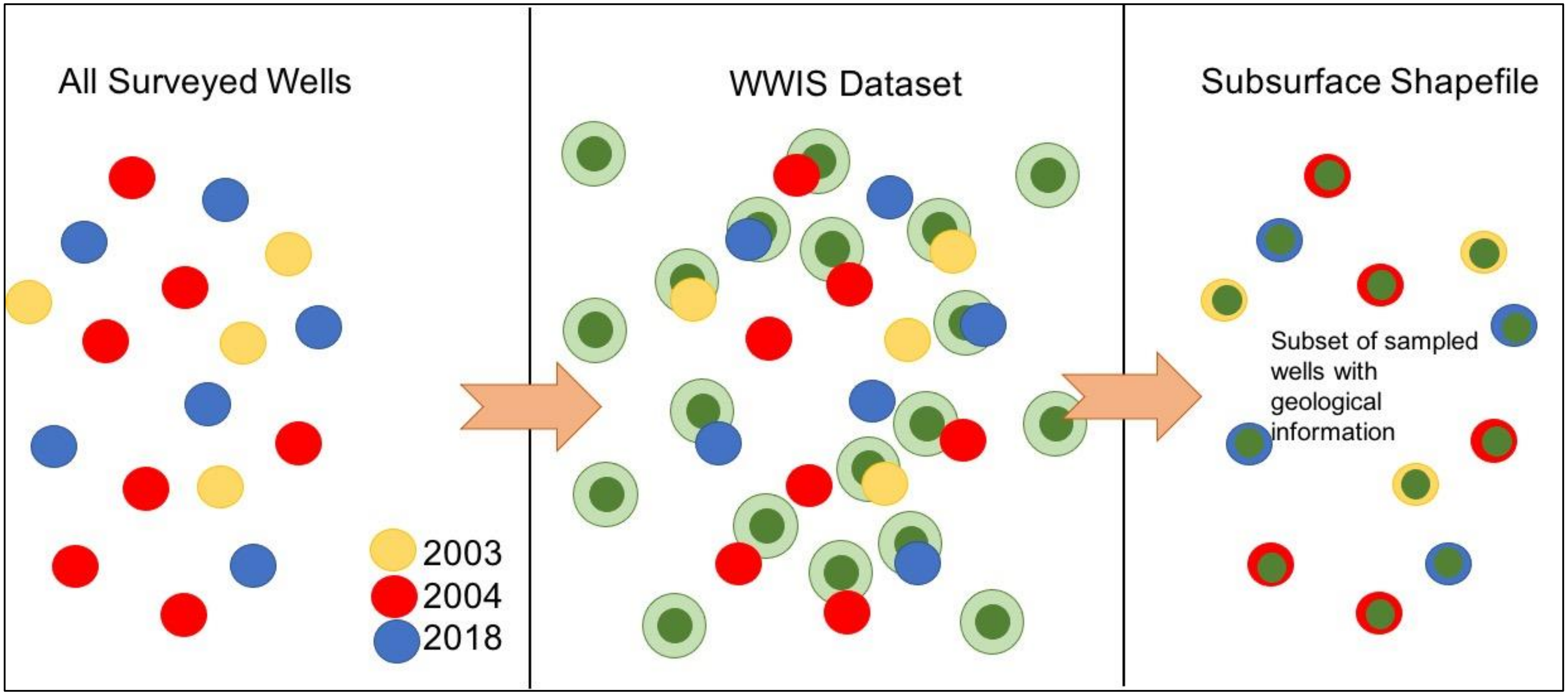


Figure 7: Process used to create subsurface shapefile. A series of 100m buffers were places around each historical well record from the WWIS dataset. Surveyed wells from 2003, 2004, and 2018 that lied within buffers were considered to be the same well as those from historical records. If multiple records or surveyed wells lied within buffer, dates were compared to identify if a match occurred. If a match could not be proven, overlapping sampled wells were omitted from the new shapefile.

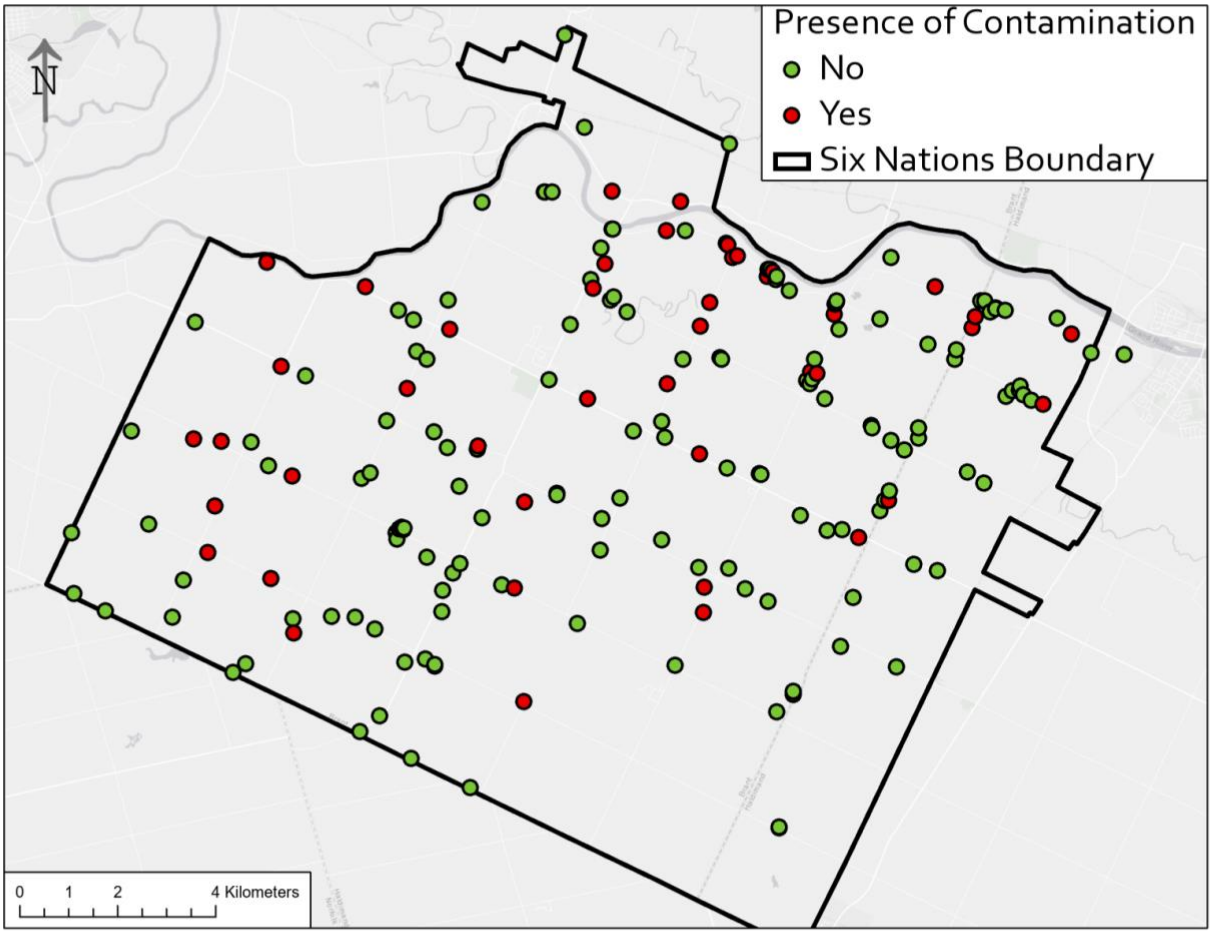
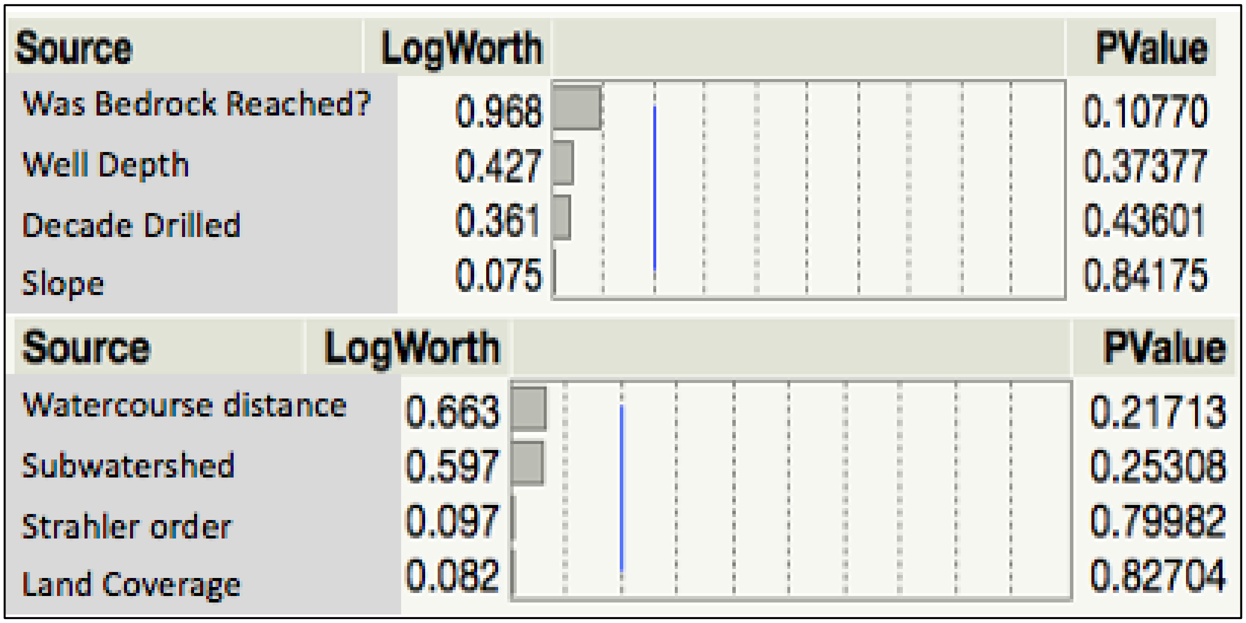


Figure 8: Presence and absence of *E.coli* contamination in sampled wells from 2003, 2004, and 2018 within the Six Nations of The grand River Reserve



Source	LogWorth	PValue
Was Bedrock Reached?	0.968	0.10770
Well Depth	0.427	0.37377
Decade Drilled	0.361	0.43601
Slope	0.075	0.84175

Source	LogWorth	PValue
Watercourse distance	0.663	0.21713
Subwatershed	0.597	0.25308
Strahler order	0.097	0.79982
Land Coverage	0.082	0.82704

Figure 9: Generalized Linear Mixed Model results for predictor variables based on subsurface data (top) and surface data (Bottom). Results indicate that no predictor variables were significant estimators for presence or absence of contamination.

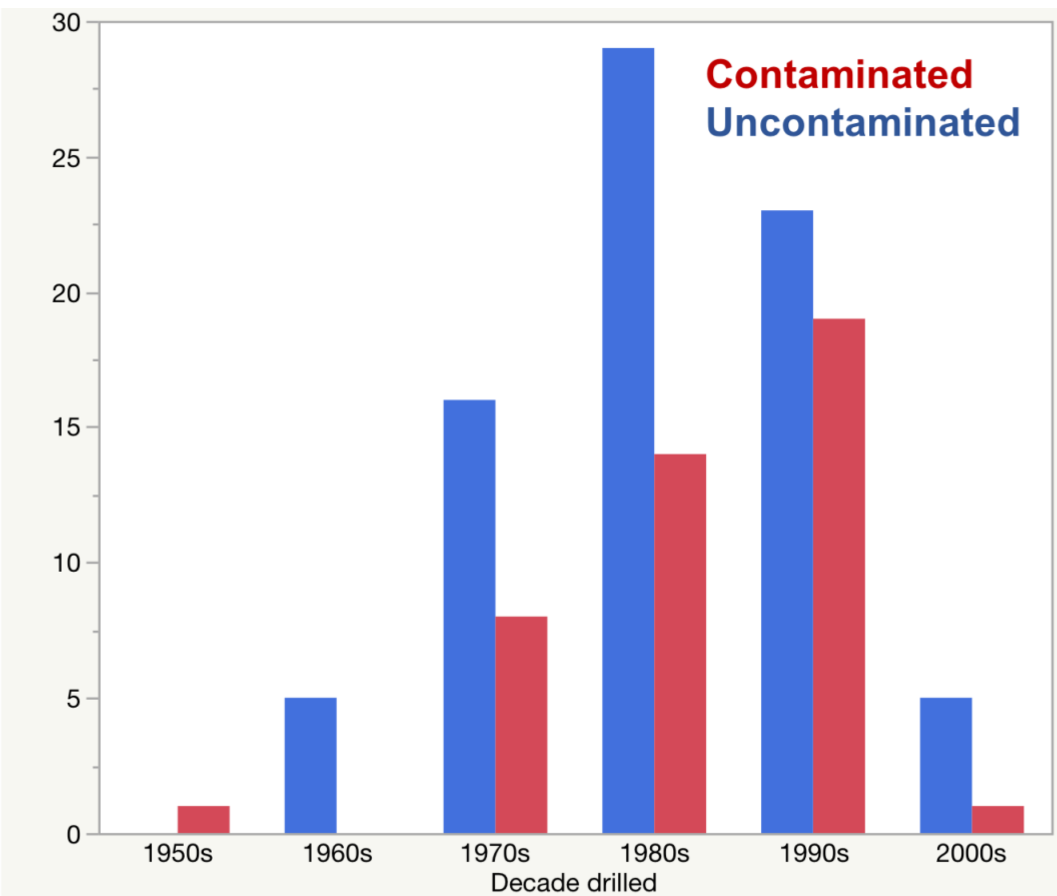


Figure 10: Comparison of contaminated and uncontaminated wells by decade drilled.

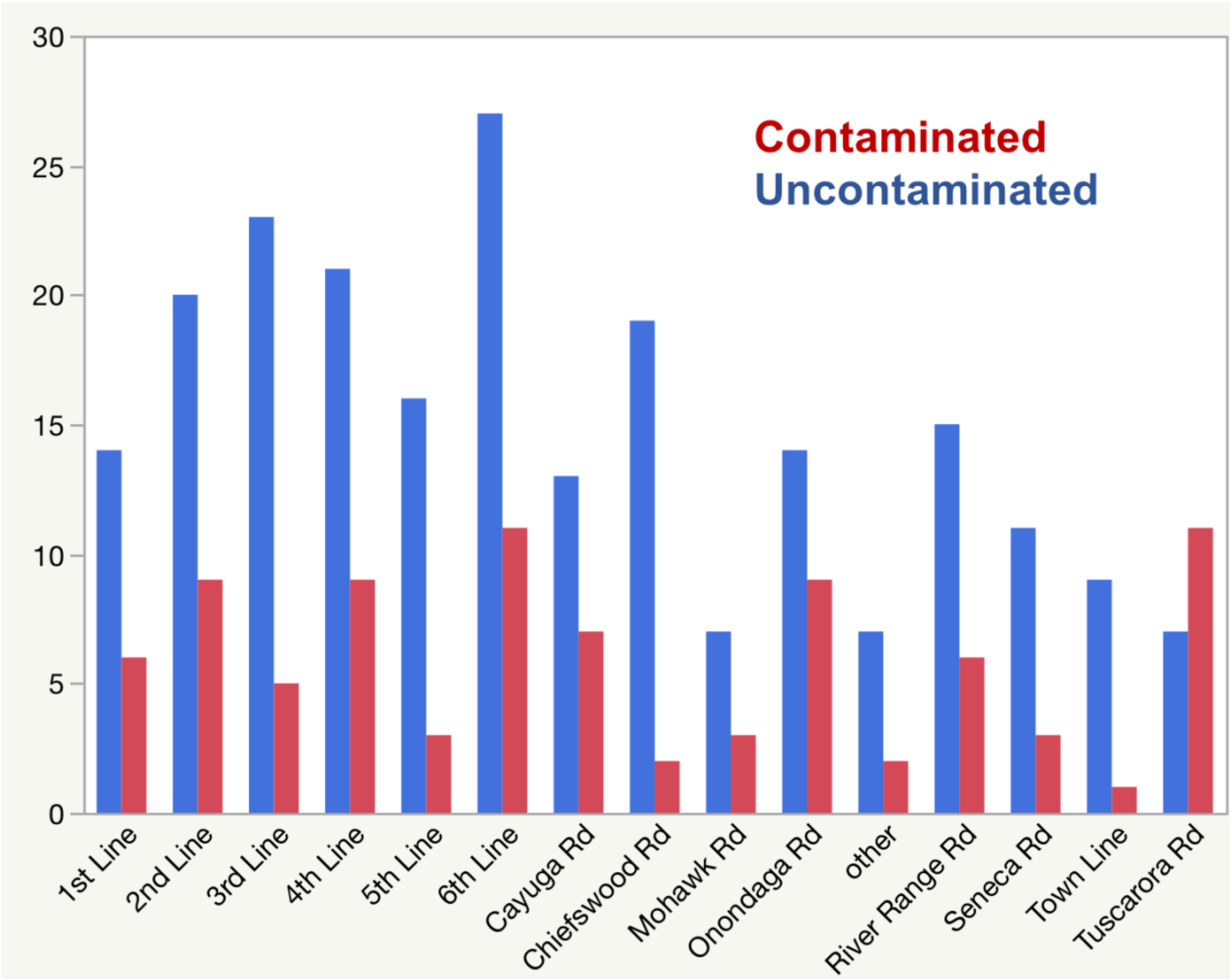


Figure 11: Comparison of contaminated and uncontaminated wells by the road that they are on.

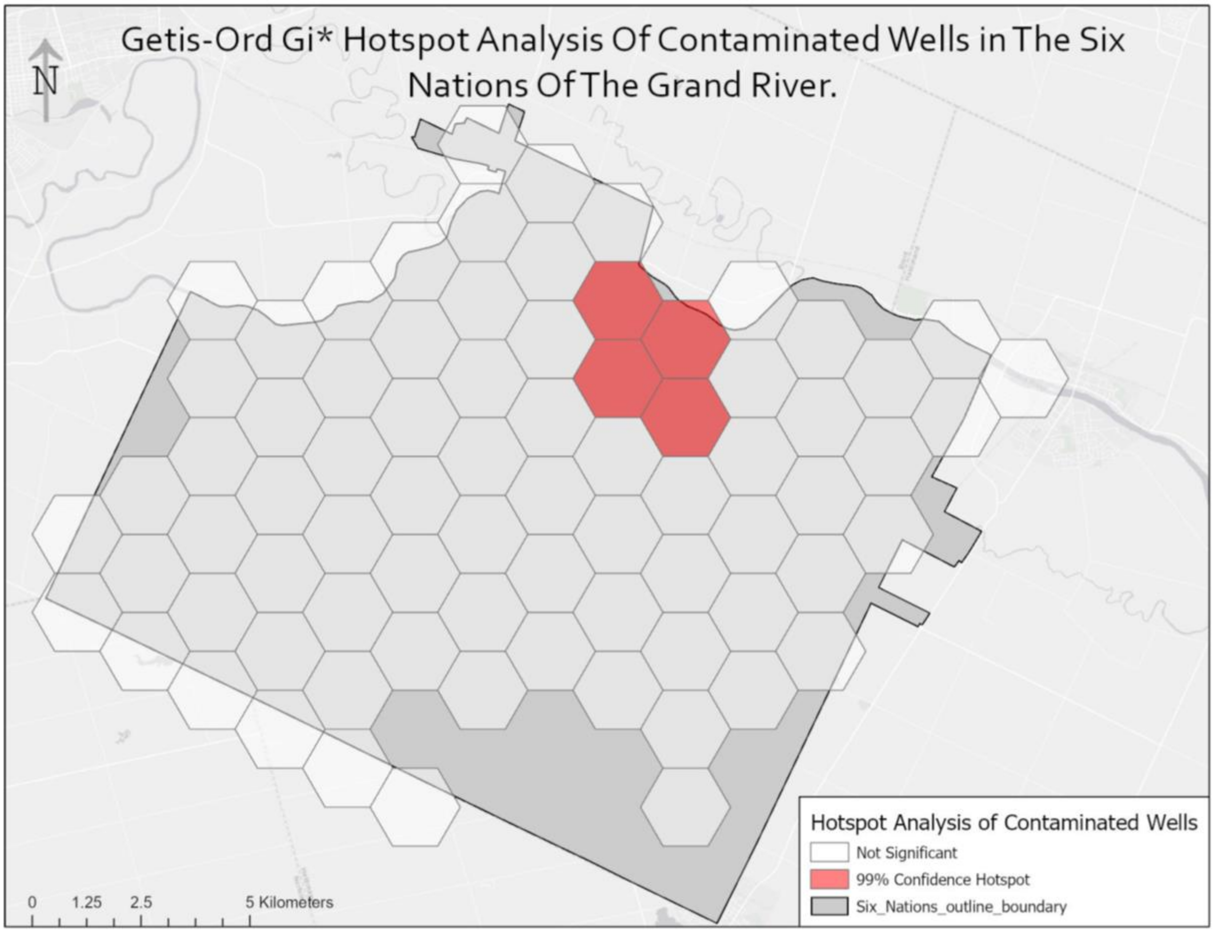


Figure 12: Advanced Hotspot Analysis of contaminated wells within the Six Nations of The Grand River Reserve.

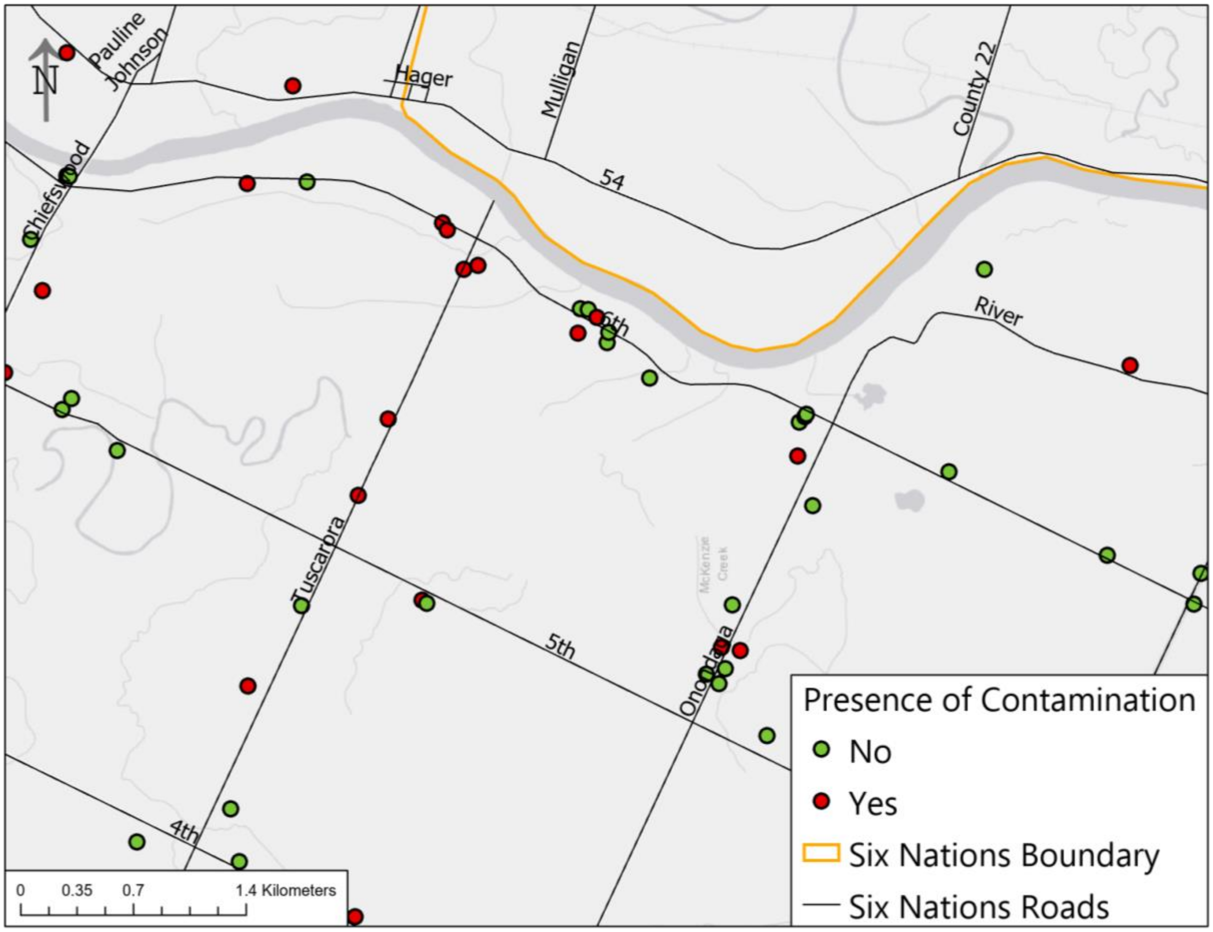


Figure 13: Uncontaminated and Contaminated wells in region of significant clustering from hotspot analysis of contaminated wells within the Six Nations of The Grand River Reserve. The corner of Tuscarora Road and 6th Line is a specific area of interest in this region, with the highest density of contaminated wells.

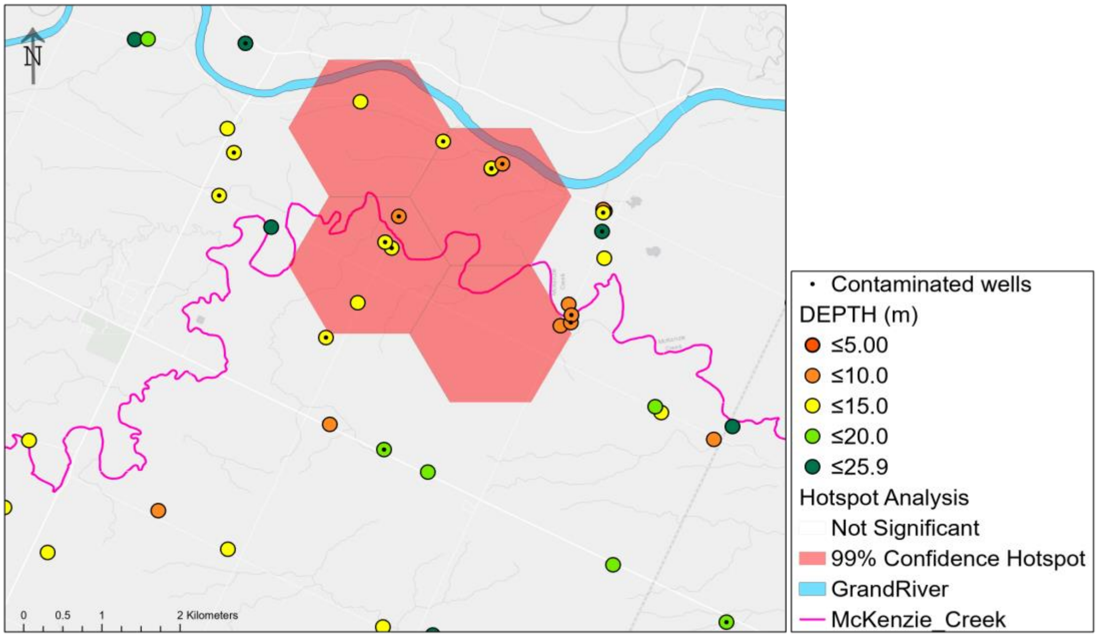


Figure 14: Depth of contaminated and uncontaminated wells in areas of significant contaminated clustering.

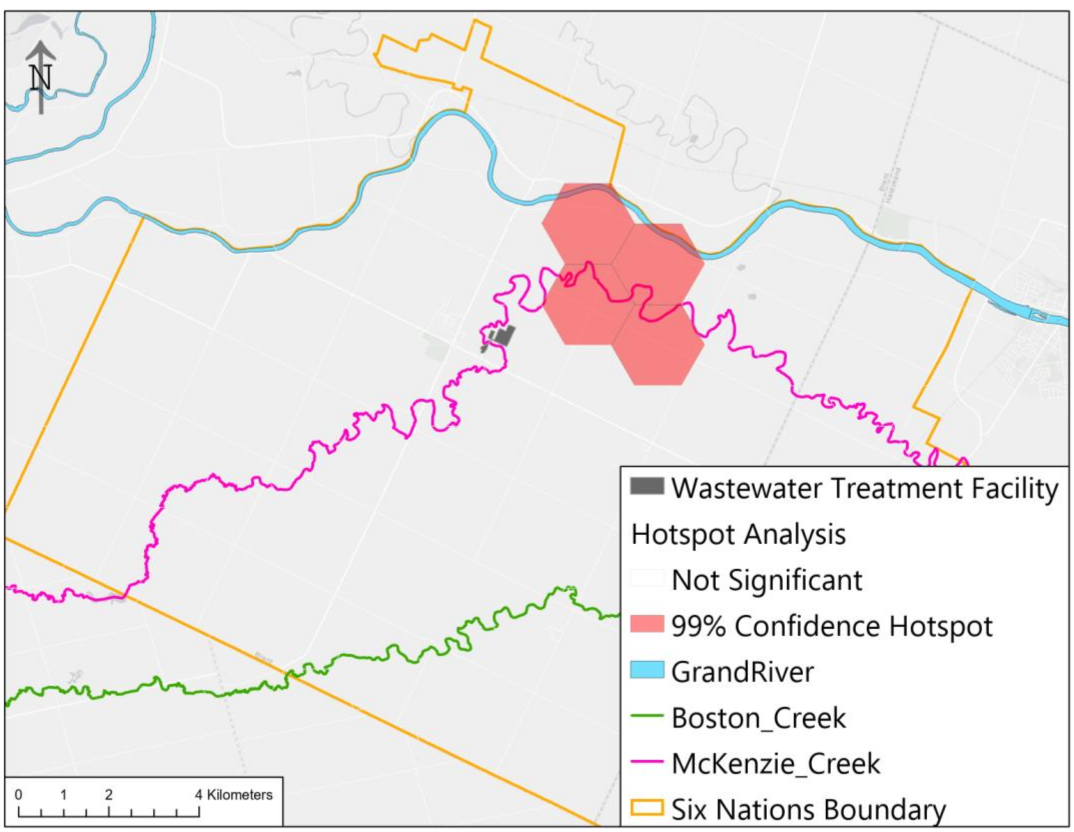


Figure 15: Watercourse flow within the Six Nations of The Grand River Reserve in relation to significant contaminated well hotspot

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