

The Effects of Dissolved Lithium in Ground Water on Violent and Property Crime Rates for Selected Texas Jurisdictions

John A. Servello
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Department of Geography, University of North Texas

Instructor: Dr. Pinliang Dong

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Abstract

Lithium, a small, light metal, can be dissolved into groundwater in cationic form (Essington 2004). It has been recognized and used as a treatment for psychological disorders since the late 1940's (Birch 1995; Schrauzer 2002). Recent research (Flannagan 2006) has suggested an inverse relationship between suicide rates and the concentration of lithium in dissolved water: increased concentrations appear to correlate with a lower number of suicides. Similarly, the same inverse relationship was observed for both violent crimes and suicides over a 10 year span (Schrauzer and Shrestha 1990). This project was conducted to further explore the relationship between dissolved lithium concentration with violent crimes (homicide, rape, assault, and robbery) and property crimes (burglary, larceny theft, and motor vehicle theft). Using dissolved lithium data gathered from the Texas Water Development Board Groundwater Database, a lithium surface for the State of Texas was developed and used to determine mean concentration (in $\mu\text{g/L}$) for each county in Texas. These data were in turn used in statistical analyses (Spearman's nonparametric correlation) with the Statistical Package for the Social Sciences (SPSS) to identify potential relationships between lithium concentration and six newly defined crime indices derived from crime data provided by the Texas Department of Public Safety. The indices were as follows: homicide, rape, aggravated assault, armed robbery, total violent crime, and total property crime. Analyses were conducted for all 254 counties in the state. Additionally, five random stratified samples ($n = 25$) of Texas cities from five non-contiguous lithium class ranges were subjected to correlation analysis for the same relationships. The results suggest that there is a relationship between lithium concentration and crime rates. Further attention to this problem is warranted.

Introduction

Lithium, the smallest ($Z = 3$) and lightest ($A = 7$ atomic mass units) alkali metal, is readily present in soil and rock in the form of minerals and ionic salts. The passage of surface or groundwater over sediments breaks away lithium compounds and dissolves them, forcing cationic lithium into solution (Essington 2004). Once released to water supplies by way of natural weathering (breakdown), this freed lithium can then be drawn into plants (trace minerals), consumed by animals (e.g., grazing livestock), and ultimately present itself in humans, the consumers of meat and water (Schrauzer 2002).

Historically, compounds found in “mineral waters” were believed to treat wide-ranging ailments. A prime local example includes Mineral Wells, Texas. During the early 1900’s, this town was a famous “health spa and resort” treating all manner of “invalids” with curative waters from multiple deep water wells. Locals claimed that mineral waters from the various wells provided cures for such common issues as diarrhea, constipation, liver torpidity, and most interestingly, “female hysterical mania” with waters drawn from the “Crazy Well.” Concentrations of dissolved lithium from this well register up to 0.17mg/L (Portal to Texas History online, Famous Waters online).

First recognized for its ability to control manic depression in 1949, lithium has been regularly used in the form of salts (e.g., lithium carbonate) for treatment in psychiatric medicine since the 1960’s (Birch 1995). Contemporary medical applications include treatment for depression and bipolar disorder. Regular dosage has been shown to deter suicide and unrestrained violence (Birch 1995; Schrauzer 2002). Although commonly used to treat mental illnesses, the mechanisms that lithium ion employs are still not fully understood. Current research suggests that the presence of lithium alters neuron membrane potential and signal transduction (Dafflon 1999).

Lithium is considered an essential micronutrient. Relatively high concentrations have been identified in developing human fetuses. It is also present in variable trace amounts in all biological samples collected from humans. Schrauzer (2002) noted a 1995 study in which rats deprived of lithium developed behavioral abnormalities.

Heavier metals, such as lead, manganese and cadmium, have been identified as neurotoxins, and have shown to be positively correlated with aggressive and/or violent behavior. Masters (1998) noted that blood and hair samples collected from incarcerated violent criminals had higher concentrations of these metals than those gathered from non-violent people. Additionally, he noted that lithium appears to have a detoxification effect on some of these heavier metals. Further, those same individuals exhibiting higher concentrations of heavy metals and greater proneness to violence provided lower concentrations of lithium than non-violent inmates.

Previous research has demonstrated significant inverse relationships between rates of violent crimes and suicides with dissolved lithium concentration in the groundwater (Schrauzer 2002). UNT Geography student William Flannagan (2006) identified a negative correlation between dissolved lithium and suicide rates in Texas counties: as lithium concentrations increased, there was a decrease in the number of suicides. Anecdotally, a 1971 article in Time magazine suggested that there could be an association between higher concentrations of dissolved lithium in the ground water and relatively low violent crime rates in El Paso, Texas. Schrauzer and Shrestha (1990)

reported this relationship after examining violent crimes and suicides in 27 Texas counties over a 10 year span.

The following project was conducted in an attempt to use both digital geographic and assorted attribute crime data to further explore potential correlations between cationic lithium in ground water and crime rates. Two hypotheses were tested:

1. Higher concentrations of dissolved lithium (in ug/L) in consumable ground water will inversely correlate with the number of reported violent crimes.
2. There is no correlation between reported property crimes and dissolved lithium concentrations in ground water

The US Department of Justice, Bureau of Justice Statistics, classifies violent crimes as murder/non-negligent manslaughter (homicide), forcible rape, armed robbery, and aggravated assault. Property crimes include burglary, larceny theft, and motor vehicle theft (USDOJ online). Using a combination of GIS techniques and statistical analyses, this project sought to identify potential relationships between the reported crimes (Violent and Property) in various jurisdictions throughout the state of Texas and the concentration of dissolved lithium in the groundwater for those jurisdictions.

Study Area and Data Sources

The study area of interest falls within the boundaries of the State of Texas. All counties and a sampled collection of variably-sized cities from around the state were analyzed. Datasets were collected from multiple online sources. All downloaded shapefiles were unprojected Geographic Coordinate System North America 1983, in decimal degrees. Figures 1, 2 and 3, presented below, have been projected (North American Datum NAD 1983, UTM Zone 14, meters). Administrative layers (shapefiles: state polygon, county polygon, city point) were acquired from the Texas Natural Resource Information System (www.tnris.state.tx.us). The city layer included both census 2000 data and 2005 population estimates, the latter of which were used during the sampling process of the project. The Texas Water Development Board (www.twdb.state.tx.us) provided access to the Texas Groundwater Database (GWDB), as well as a point shapefile for sampling wells distributed around the state. Updated by TWDB at monthly intervals, the GWDB (personal database) provides information in tabular format for all sampling wells in the state. These include tables on water level, well construction material, the water quality, qualitative descriptions of sampled water (e.g., color, odor), and quantitative measures of both frequent and infrequent constituents found in the wells. This project focused on infrequent constituent data (dissolved lithium) recorded between 2000 and 2006. Crime data for 2006, the most current available, were accessed through the Texas Department of Public Safety Division of Crime Records (<http://www.txdps.state.tx.us>). The 2006 cumulative crime report breaks down crime statistics for each individual reporting law enforcement jurisdiction (city police departments and county sheriffs' offices) within a given county. Available information included the raw counts for all violent and property crime sub-categories (listed above), the estimated 2006 population, and crime rates per 100,000

people. Additional county-wide aggregates were provided by DPS as well. Ancillary population demographic data were acquired through the US Census American Community Survey (www.census.gov).

Methodology

The Infrequent Constituents table located in GWDB was added to ArcMap. Measured infrequent constituents are identified under the “Storet_Code” field; wells registering dissolved lithium had an assigned a code of “01130,” with the corresponding concentration reported in $\mu\text{g/L}$. Recorded samples dated from 1939 to present. Records with an associated code of 01130 were selected and exported as a new table. A portion of this table is available in **Appendix I**. Sampling years 2000 through 2006 were further selected and exported. Following, the table was summarized by the concentration on the well identification field, providing a newly exported table (see **Appendix II**) of average lithium concentration per well for the six year span ($n=4775$).

Multiple layers were then added to the Display, including polygons for county ($n=254$) and state, as well as city ($n=1206$) and well point layers. The average lithium table was joined to the well shapefile, which comprised all sampling wells ($n=133159$) for the state. Wells for that layer with the 01130 store code value (joined field) were selected and exported as a new shapefile (wells with a recorded average lithium concentration, $n=4775$, see **Fig. 1** below). The Inverse Distance Weighted interpolation method was used to generate a continuous lithium surface for the state. Lithium wells were set as the input, with the concentration field listed as the z value. The output extent was set to match the State polygon layer. Interpolation was based on a variable search radius for 16 points (wells). The output cell size was 0.04. The surface was then extracted using the Texas layer as a mask (see **Fig. 2** below).

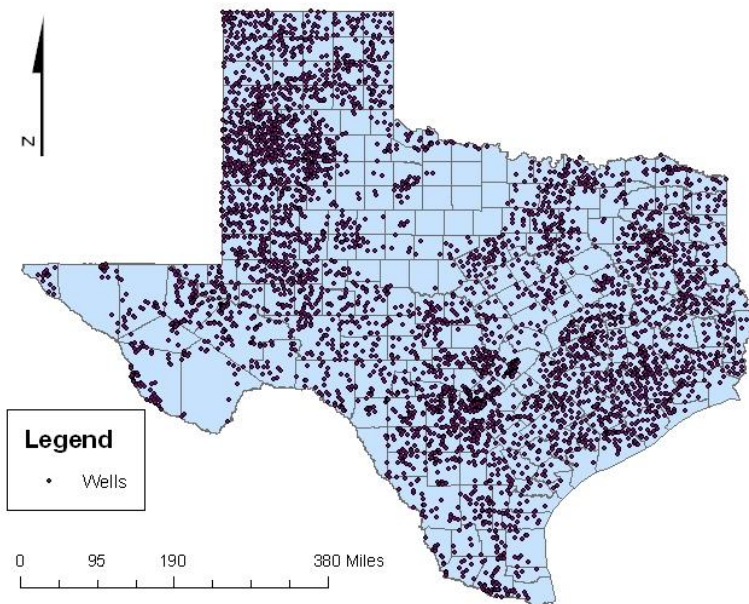


Figure 1. Sampling wells distributed throughout the State of Texas. Wells represented ($n=4775$) register dissolved lithium. Concentrations associated with each well point are recorded as six year (2000-2006) averages.

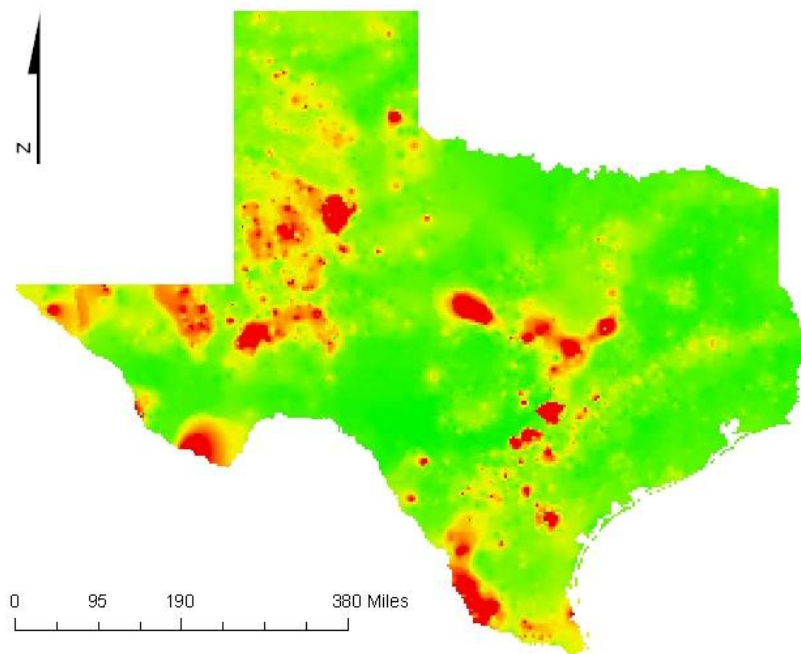


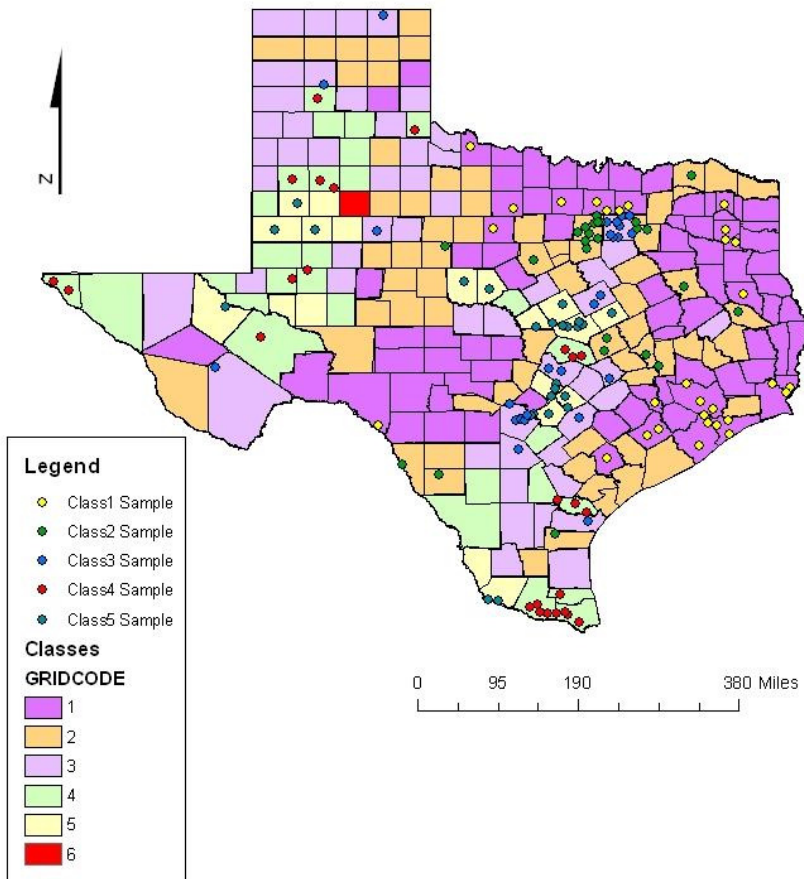
Figure 2. Continuous lithium concentration across the state. Interpolated from concentration data associated with wells (Fig. 1 above) using IDW technique. Display scale is from low concentration (green) to high (red).

An average concentration for each county was then determined. The Zonal Statistics option was selected, using the county layer as a feature zone, the zone field set to the county Federal Information Processing Standard (FIPS) code, and the lithium surface input as a value raster. Mean county concentrations ranged from roughly 4.0 to 688.1 $\mu\text{g/L}$. The output raster was then reclassified into six natural breaks, non-contiguous classes, 1 through 6 (representing low to high concentration). Defined classes represented the following lithium concentration ranges: Class 1, 3.99 to 30.7 $\mu\text{g/L}$; Class 2, 30.7 to 60.1 $\mu\text{g/L}$; Class 3, 60.1 to 91.6 $\mu\text{g/L}$; Class 4, 91.6-134.7 $\mu\text{g/L}$; Class 5, 134.7-280.3; $\mu\text{g/L}$; and, Class 6, 280.3-688.1 $\mu\text{g/L}$. The resultant raster was then converted to a Class polygon layer (**Fig. 3**).

The county polygon layer, with name labels active, was overlaid with the average concentration raster. Setting the raster as the active layer, the Identify tool was used to acquire concentration values for each county. These values were subsequently entered into the attribute table for the County layer in an Editor session.

The Class polygon was used to isolate cities that fall within each class. Class 6, represented the highest lithium concentration (688.1 $\mu\text{g/L}$). This Class consisted of only one sparsely populated county (Garza, under 5000) and one town (Post). A representative sample could not be collected from this class; therefore it was excluded from further analysis as an outlier. The next highest concentration was 280.3 $\mu\text{g/L}$ (Caldwell County), falling in Class 5. Using Select by Location, cities falling within each of the five remaining classes were selected and exported into new point files for each class: Class 1 n=483; Class 2=291; Class 3 n=227; class 4 n=128; and, Class 5 n=72.

A representative sample of towns from each class was arbitrarily set to be size $n=25$ (± 2). The attribute table for each unsampled group of cities was sorted, ascending by the population 2005 (estimated) field. A new field (Random) was then added and populated with integer values ($1 \rightarrow n$) for each record. Each table was arbitrarily broken down into six strata, based on the 2005 estimated population: 0-4999; 5,000-24,999; 25,000-49,999; 50,000-99,999; 100,000-499,999; and, greater than 500,000. Towns with fewer than 5000 people were excluded because it was believed that social control mechanisms would have a greater affect on the citizens in these smaller communities. Additionally, the rare violent crime (e.g., homicide) in one these communities would greatly inflate the related index value (crime analysis is described below) determined for the community. The composition of the sample was then determined by the following process: the remaining cities (populations 5000 or greater) were each selected by stratum and counted. Next, the proportion of cities in a stratum to the total number of cities within the class was determined. This proportion was then multiplied by 25 and rounded to the nearest integer to get the exact number of cities to be sampled from one stratum. The Random value ranges for each stratum were then recorded and entered into a random number generator (<http://www.randomizer.org/>). The output set of values produced by the generator were used to select and export cities as Sample Class point layers (Fig. 3).



The crime data acquired from DPS were originally in PDF format and required extensive data entry. These crime data were compiled in two ways: by county and by sampled cities. The county data were recorded into a Microsoft Excel spreadsheet. The records consisted of aggregated data for all reported law enforcement jurisdictions by county, including raw counts for each violent crime subtype (homicide, rape, aggravated assault, and armed robbery) and total property crime (burglary, larceny theft, and motor vehicle theft). Also added was a field the total estimated population for 2006. The completed table was imported into ArcCatalog, joined to the County polygon layer (access to the averaged lithium concentration), and subsequently exported.

The sampled city crime data were added to the five Class Sample attribute tables. Similar to the County crime data, new fields were added for each violent crime sub-category, total property crime, and estimated 2006 population for each city. Additionally, a county name field was added. Any city that crossed county lines (e.g. Austin, Houston, and Denton) was assigned to the county in which the majority of that city was located. The fields were populated during an Editor session. Each table was joined to the County polygon layer table (for the lithium concentration field) and exported.

All six exported tables were opened. Unnecessary or repeated fields were deleted. Six new fields were added for original indices developed for the project. These included the following: homicide index; rape index; robbery index; aggravated assault index; total violent crime index; and, total property crime index. Law Enforcement agencies, including DPS and the Department of Justice, generally report crimes as incidences in 100,000. These indices were calculated by determining the proportion of a given category (e.g. homicide) to a local population (city or county, dependent upon the table) multiplied by a constant (10,000), effectively putting all sampled towns and cities, regardless of size, on the same scale. Because many of these indices were significantly less than one, the large constant was arbitrarily selected to inflate the small index values to make any variability more apparent during the data review.

Tabular crime data for City and County were subjected to Spearman's Ranked Correlation analysis using customized programs for the Statistical Package for the Social Sciences (SPSS). Spearman's Correlation, a bivariate, non-parametric analysis, is used for data samples that are characterized as having non-normal distributions. Each of the variables of interest is ranked (1→n). Like parametric (Pearson's) correlation, Spearman's tests for a relationship between the variables. Further, significant correlation (positive or negative) does not necessarily dictate causality. The County data were analyzed for separate correlations between each ranked index and the ranked lithium concentration. Similarly, the City data were examined for relationships between ranked indices and ranked concentrations associated with the city host county.

Results and Preliminary Discussion

County indices were initially analyzed with the SPSS. Results are presented below in **Table 1**. There was a highly significant inverse association (Spearman's ranked

correlation, $r_s = -0.187$, $p = 0.003$). Although the remaining five indices exhibited negative relationships with concentration, none were statistically significant.

Table 1. Spearman's correlation ($\alpha=0.05$) results for six crime index-lithium concentration pairings, County level analysis ($n = 254$).

Lithium concentration correlation with:	r_s	Probability
Homicide index	-0.187	0.003
Rape index	-0.023	0.71
Aggravated assault index	-0.077	0.22
Armed robbery index	-0.117	0.06
Total violent crime index	-0.082	0.19
Total property crime index	-0.051	0.72

Correlations between sampled city data and concentration are presented in **Table 2**. Significant negative correlation was observed between the homicide index and lithium concentration, as seen with the county data. The city data then diverged. Inverse relationships between concentration and total violent crime index and the property crime index were significant. A positive association was observed with the robbery index. Further, there was a highly significant negative relationship between the aggravated assault index and lithium concentration ($r_s = -0.55$, $p < 0.0001$). A negative relationship between rape and concentration was not statistically significant.

Table 2. Spearman's correlation ($\alpha=0.05$) results for six crime index-lithium concentration pairings, City level analysis ($n = 125$).

Lithium concentration correlation with:	r_s	Probability
Homicide index	-0.190	0.033
Rape index	-0.095	0.291
Aggravated assault index	-0.553	<0.0001
Armed robbery index	+0.184	0.040
Total violent crime index	-0.189	0.035
Total property crime index	-0.213	0.017

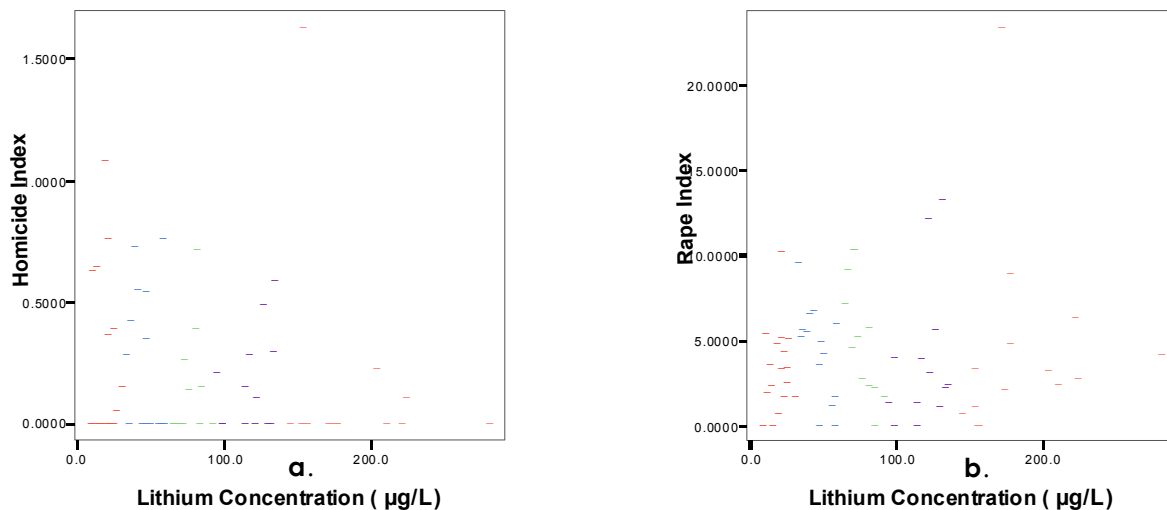
Failure for the county analyses results to not better reflect those observed for the cities, or *visa versa*, was unexpected. There are multiple possible explanations for this. First, all counties (254) were used for the first level of analysis. Many of these are sparsely populated, consisting of small communities (less than 5000) which were excluded from the sampled city analyses. Non-significant relationships may be due to the fact that smaller communities were over-represented in the county analysis. Likewise, absence of these towns may have inflated the significant relationships observed within cities over 5000. The sampled cities ($n = 125$) with populations greater

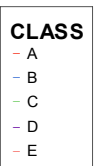
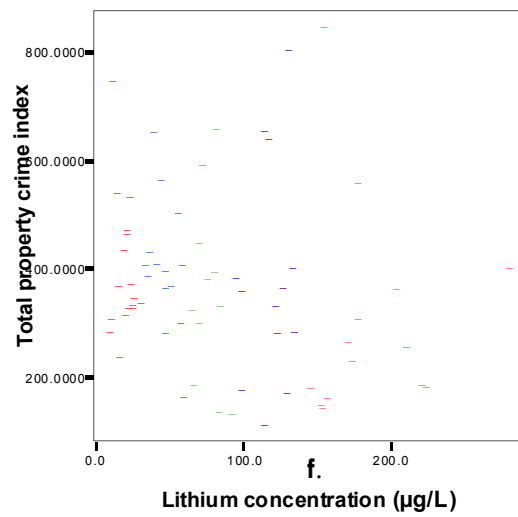
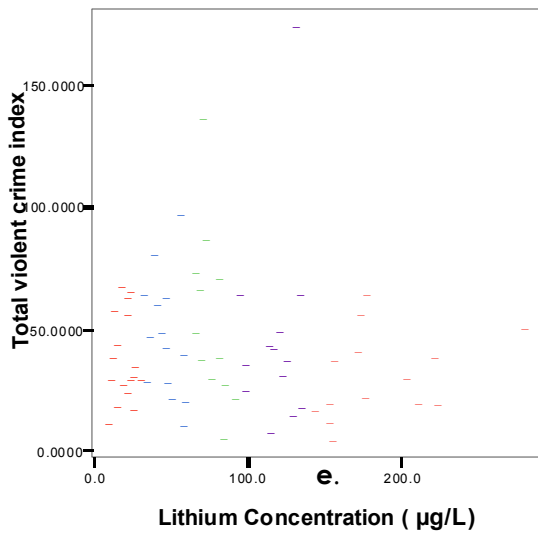
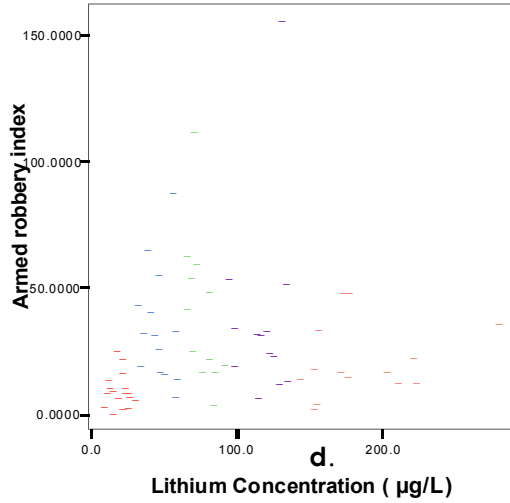
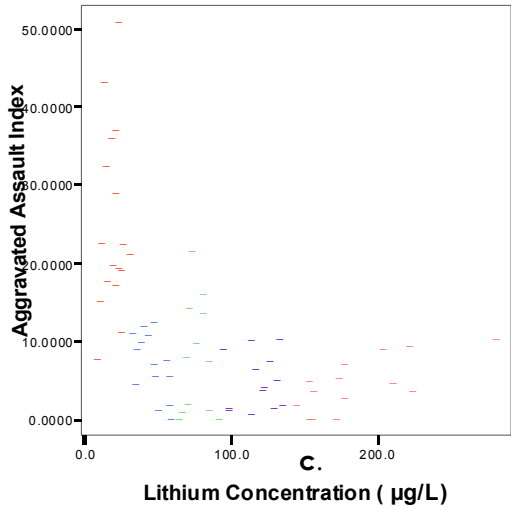
that 5000 were pulled from only 73 counties located around state. If the smaller communities from those additional counties had been included, city results may have approximated those at the county level. Lastly, suburbs and “bedroom communities” surrounding the larger metropolitan areas of the state, particularly for Classes 2 (Fort Worth) and 3 (Dallas, San Antonio), may have been over-represented.

The statistical relationships defined in Table 2 above are better revealed graphically in **Fig. 4a-f** (see below). When each of the index values is plotted against lithium concentration, an overall decrease in index value by class is observed as concentration increases. The exception to this is the armed robbery (**4-d.**) index plot, which demonstrates a positive association. Plot **4-a** (homicides) contains many index values equal to zero. These points primarily represent sampled communities with smaller populations (5,000 to 10,000 people) that registered no homicides in 2006. This supports the exclusion of those communities with less than 5000 people: violent events such as homicide are generally rare in these communities. By ignoring the zero points along the *abscissa* (treating them as “noise”) and examining the remaining points, a clear negative relationship can be observed.

The aggravated assault plot (**4-c**) shows a clear decrease in index value as concentration increases. Further, this relationship breaks down by class. Casual observation suggests that this trend may be nonlinear. Unfortunately, because the analysis is on ranked data, testing for a logarithmic association would not be appropriate. The remaining two plots that display significant relationships (**4-e, 4-f**) are more difficult to interpret. There appears to be a slight negative association between the total violent crime index and concentration (**4-e**), although the point spread for Classes 2 and 3 obscure this. The total property crime index also appears to decrease, although this is difficult to argue due to the wide point ranges for all five classes.

Figure 4. Scatterplots for lithium concentration comparison to indices for a) Homicide, b) Rape, c) Aggravated Assault, d) Armed robbery, e) Total violent crime, and f) Total property crime. Points are plotted by class. A legend is provided with f). Each index demonstrated a significant inverse association with concentration except for the rape index ($r_s = -0.095$, $p = 0.29$).





Conclusions

The preceding study was conducted in an effort to determine if there was an inverse relationship between rates of violent crime and the concentrations of dissolved lithium in drinking water. Sampling wells located throughout the state were used to generate a continuous surface, which was ultimately broken down into two layers: mean lithium concentration by county, and five non-contiguous classes. Using the first, counties were examined as a group for associations between crimes indices and dissolved lithium concentration. The second raster was used to sample cities falling in each of the classes. Sampled cities were also examined, as a group, for associations between reported crime indices and concentration. The analyses revealed that although there was a statistical inverse relationship at the county level between homicides and lithium concentration, no other index-concentrations were significant. Conversely, the city level provided statistically significant relationships for each index-

concentration pairings save for the occurrence of rape. These analyses suggest that there may be a relationship between the dissolved lithium levels in water and reported crime rates.

Although nonparametric correlation analysis suggested relationships between lithium concentration and crime, there are other confounding factors that were not explored in this project. Population density was not applied as a variable in this study, although it is likely an important factor: increases in population density generally reflect higher corresponding crime rates. Houston and Denton, two cities sampled from Class 1, are presented as examples. Based on a projected 2006 population of 2,016,582, the population density for Houston would be 3641.3/sqmi. Houston registered 376 homicides for 2006. The corresponding homicide index is 1.813, with a total violent crime index of 116.9. This may be contrasted with Denton, projected population size of 104,153 (density = 1741.5/sqmi), which recorded no homicides that year, and revealed a total violent crime index of 30.7.

Similarly, Class 5, representing counties with the highest concentrations of dissolved lithium, consisted of 72 total communities, 47 of which had less than 5000 people and were excluded. The remaining 25 comprised the entire Class 5 sample (i.e., this was the one sample that could not be generated randomly). Caldwell County recorded the highest lithium concentration (280.3 μ g/L). Two towns were sampled: Luling (2006 population at 5,539) and Lockhart (13,951). Neither registered homicides that year, but both provided total violent crime index values higher than Denton (55.2 and 45.1, respectively) due to relatively high number of aggravated assaults (13 and 67). Assaults reported by police could be any type of altercation, ranging from bar fights to flatulating in the direction of a State of West Virginia police officer (this charge was later dropped). This suggests that for the purpose of this and related studies, perhaps violent crimes should be limited to homicide and rape.

Additionally, although groundwater lithium concentration was studied for this project, many areas in the state, especially densely populated metropolitan areas (e.g., Dallas-Fort Worth) consume other sources of water, including surface (e.g., reservoirs and rivers) or bottled products. Future studies should focus on identifying where different jurisdictions specifically obtain potable water. When those sources have been identified, the corresponding infrequent constituents (e.g., dissolved lithium, if any) for these jurisdictions must be included with respect to crime correlation. Such data were not available for this study and could not be pursued.

Lastly, underlying population demographics is likely influencing crime. The city of El Paso sparked the initial interest in this project due to its large population size (615,553), fairly low crime rates (13 homicides, index = 0.211, total violent crime index of 39.4). Per the US Census 2006 Community Survey, the city is 82% Hispanic. This raises the following question: does population demographic homogeneity produce lower levels of violent crime observed in El Paso? Houston by contrast has not only higher corresponding crime rates, but the population is also more heterogeneous (42% Hispanic, 28% white, 24% black, remaining 6% in other categories; US Census 2006 Community Survey). Oversampled suburbs from Classes 2 and 3, mentioned in the results section, are likely more homogenous than the cities that they feed. Future research should examine the demographic effects, as well as population density and

non-groundwater sources, to determine whether when combined with dissolved lithium influence crime rates.

Further study into the relationship between dissolved lithium and crime is warranted. Additional research will need to include larger samples of cities; smaller towns (less than 5000 people) should be included. This study focused only on groundwater and future projects will require that all potable water sources must be identified for any sample city, including surface sources. Lastly, both the population density and underlying demographics of a city likely play a part in crime rates. Additional research should focus on how all of these variables, as well as dissolved lithium, affect crime rates.

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Texas Natural Resource Information System online. www.tnr.is.state.tx.us

Texas Water Development Board online. www.twdb.state.tx.us

United States Census Bureau online, ACS Demographic Housing Estimates, American Community Survey 1-Year Estimates. www.census.gov

Appendix I. Table Subset: All well samples registering lithium, 2000-2006.

OID	OBJECTID	state_well	mm_date	dd_date	yy_date	sample_num	storet_cod	const_val
0	22	140301	5	18	2004	1	01130	20.8
1	68	140601	6	26	1996	1	01130	17.4
2	101	140906	5	14	2008	1	01130	101
3	131	140906	5	18	2004	1	01130	41.2
4	157	140906	6	25	1996	1	01130	19.8
5	182	140906	8	1	2001	1	01130	25.6
6	209	148303	8	2	2001	1	01130	31.1
7	268	156309	5	12	2000	1	01130	24.9
8	292	156309	5	19	2008	1	01130	70.1
9	342	156906	5	12	2000	1	01130	28.5
10	366	156906	5	15	2008	1	01130	99.3
11	396	233201	5	15	2000	1	01130	30.4
12	420	233302	5	14	2008	1	01130	67.2
13	450	233302	5	19	2004	1	01130	28.6
14	476	233401	5	16	2000	1	01130	36.7
15	501	233401	5	18	2004	1	01130	38.8
16	539	233701	5	15	2000	1	01130	40.0
17	565	233701	6	25	1996	1	01130	36.7
18	589	233702	5	14	2008	1	01130	124
19	619	233702	5	18	2004	1	01130	47.2
20	645	233915	5	14	2008	1	01130	90.6
21	675	234301	8	1	2001	1	01130	29.1
22	725	234302	6	25	1996	1	01130	28.6
23	751	234502	6	26	1996	1	01130	50.5
24	776	234710	5	10	2000	1	01130	59.4
25	802	234710	6	20	1996	1	01130	64.9
26	848	234711	5	19	2004	1	01130	55.9
27	874	234711	6	20	1996	1	01130	48.5
28	900	234711	8	1	2001	1	01130	84.9
29	928	234712	5	19	2004	1	01130	53.3
30	952	234712	5	20	2008	1	01130	103
31	983	235204	5	10	2000	1	01130	129
32	1008	235204	5	15	2004	1	01130	102
33	1032	235204	5	16	2008	1	01130	191
34	1063	235204	6	21	1996	1	01130	114.7
35	1088	235205	5	15	2004	1	01130	54.7
36	1113	235205	5	16	2008	1	01130	93.8
37	1145	235205	6	24	1996	1	01130	54.6
38	1171	235205	8	2	2001	1	01130	58.2
39	1251	236601	6	7	2000	1	01130	96.1
40	1295	236602	5	15	2004	1	01130	75.0
41	1319	236602	5	16	2008	1	01130	120
42	1350	236602	6	19	1996	1	01130	66.8
43	1375	236701	5	15	2004	1	01130	132
44	1399	236701	5	19	2008	1	01130	218
45	1439	236701	6	24	1996	1	01130	138
46	1464	236702	6	7	2000	1	01130	203
47	1510	237201	6	7	2000	1	01130	52.5

Appendix II. Table Subset: Average lithium concentration (2000-2006) per well.

OID	state_well	Cnt_state_	Ave_CONCEN	Well_Num ^
0	140301	1	20.8	140301
1	140906	2	33.4	140906
2	148303	1	31.1	148303
3	156309	1	24.9	156309
4	156906	1	28.5	156906
5	233201	1	30.4	233201
6	233302	1	28.6	233302
7	233401	2	37.75	233401
8	233701	1	40	233701
9	233702	1	47.2	233702
10	234301	1	29.1	234301
11	234710	1	59.4	234710
12	234711	2	70.4	234711
13	234712	1	53.3	234712
14	235204	2	115.5	235204
15	235205	2	56.45	235205
16	236601	1	96.1	236601
17	236602	1	75	236602
18	236701	1	132	236701
19	236702	1	203	236702
20	237201	1	52.5	237201
21	237602	1	57.6	237602
22	238401	2	55.6	238401
23	239101	2	133	239101
24	239401	1	62.5	239401
25	239605	1	62.8	239605
26	239701	1	61.3	239701
27	241303	1	34.6	241303
28	241503	2	74.25	241503
29	242704	1	46.4	242704
30	243402	2	135	243402
31	243601	1	63.3	243601
32	243701	1	72.5	243701
33	244801	1	77.8	244801
34	245502	1	52.6	245502
35	246702	1	60.4	246702
36	246801	1	58	246801
37	246802	1	199	246802
38	247101	2	42.1	247101
39	248107	1	52	248107
40	248703	1	69.3	248703
41	249601	1	29.5	249601
42	250101	1	39.7	250101

Record: 1 Show: All Selected Records (0 out of 4775)