



Predicting West Nile Virus Incidence in ND using Machine Learning Techniques

PROJECT PARTICIPANTS

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Project Objectives

GOALS

Develop an user Interface showing history of North Dakota cases on West Nile Virus and Culex Species Type by categorize risk levels

- The interface utilizes multilayered Google Maps developed through Google Fusion Tables
- An understanding of historical data and weather variables is essential for providing sufficient lead time to predict WNV occurrence, and for implementing disease control and prevention strategies such as spray period and hiring of seasonal mosquito workers.

Develop a Forecasting Model to predict mosquito counts and WNV Incidence using Weather, and prior years of mosquito trap count data.

NASA Relevance

Use Remote sensing, weather data sets, "Better Understand Earth"

Methodology

Data Collection Data Organization

- Receive data from county mosquito control, NDDoH
- Integrate Weather data
- Organize data to useful format
- Clean data etc..

Analysis and Forecasting

- Basic statistical examination
- Feature selection
- Forecasting algorithms
- Accuracy assessment

Data Visualization Analysis Web Integration

- Easy interactive web interface
- Basic analysis



- Decision-making protocols
 - hiring of seasonal mosquito control units
 - public health awareness campaigns

Data Collection, Aggregation

Data must be organized to be used and interpreted

Data comes from many sources in many formats making for a time consuming challenge

	А	В	С	D	Е	F	G	Н	1	J	K	L	М	Ν
1	Weekly Mo	squito Trap Cou	unts											
2	Dates: July	v 1st - July 7th 2	013											
3	Counties	Trap Location	Male				Total Mosquitoes							
4				Anop- heles	Aedes	Aedes vexans	Culex	Culex Tarsalis	Culex salinarius	Culiseta	Other	Total Female		
5						Re	gion I							
6	Williams	Williston #1	0	0	0	2	3	0	0	0	0	5	5	
7	Williams	Williston #2	80	0	48	104	16	0	0	72	0	240	320	
8	Williams	Tioga										0	0	
9	Divide	Crosby	96	0	80	64	24	0	0	56	0	224	320	
10	McKenzie	Watford City										0	0	
11	Mountrail	Stanley										0	0	
12	Region I Tota	l	176	0	128	170	43	0	0	128	0	469	645	
13						Reg	jion II							
14	Ward	Minot Oak Park(1)	12	0	20	0	0	0	0	3	0	23	35	
15	Ward	Minot NW (2)	2	0	16	0	0	0	0	11	0	27	29	
16	Ward	Ryder	8	0	14	6	0	4	0	4	0	28	36	
17	Bottineau	Bottineau	6	2	13	1	0	0	0	1	0	17	23	
18	Burke	Bowbells	40	4	96	44	8	0	0	12	0	164	204	
19	McHenry	Towner	8	0	12	4	4	0	0	0	0	20	28	
20	McLean	Deep Wtr Creek Bay	TWTC									0	0	
21	McLean	Washburn	8	0	12	0	4	0	0	0	0	16	24	
22	Renville	Mohall	80	32	224	32	0	16	0	16	0	320	400	
23	Sheridan	Martin										0	0	
24	Region II Tota	al	164	38	407	87	16	20	0	47	0	615	779	
25						Reg	jion III							
26	Ramsey	Devils Lake #1	4	0	20	22	10	2	0	10	0	64	68	
27	Ramsev	Devils Lake #2	12									0	0	
-	She	sneet2 Si	leet3	(+)										

Sample trap count data set from ND DoH



A	В	С	D	Е	F	G	Н			J	K	L	М	Ν	0	Ρ	Q	R	S	Т	U	٧	\forall	Х	Y	Ζ	AA	AB	AC	AD	AE	AF	AG	AH	AL	AJ
Counties	Trap.Location	Male A	Anop.heles	Aedes	Aedes.vexans	Culex	Culex.Tars	alis Culex	k.sali Ci	uliseta O	ther Total	.Female T	otal.Mosqui	Week.Start	Week.End	Year	Week, M	axTemp i	MinTemp	AvgTemp F	Rainfall	AvgRain (MaxHumidi N	1inHumid	AvgHumid	WindDirl	AvgWind M	1axWind	MeanMaxTemp N	MeanMaxHumidity a	vgCT	jantemp	ebtemp	marchter ar	priltemp n	maytemp
Grand Fo	k Grand Forks #1	136	8	11,	2 80	0		0	0	72	0	272	408	5/31/2005	6/6/2005	2005	1	89	51	70.28571	0.6	0.0857	100	21	68.4286	89.86	7.7143	28	82.57142857	93.71428571	0	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #2	23	1	1	7 18	0		0	0	41	0	77	100	5/31/2005	6/6/2005	2005	1	89	51	70.28571	0.6	0.0857	100	21	68.4286	89.86	7.7143	28	82.57142857	93.71428571	0	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #1	108	10	164	4 108	0		0	0	152	0	434	542	6/7/2005	6/12/2005	2005	2	76	50	63	2.7	0.45	100	46	78.1667	158.7	10.333	38	71.33333333	98.16666667	0	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #2	10	2	58	B 40	0		0	0	58	0	158	168	6/7/2005	6/12/2005	2005	2	76	50	63	2.7	0.45	100	46	78.1667	158.7	10.333	38	71.33333333	98.16666667	0	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #1	30	0	56	6 64	0		0	0	8	0	128	158	6/13/2005	6/19/2005	2005	3	88	52	67.42857	0.78	0.1114	100	41	75.7143	158.6	9.2857	30	76.14285714	92.71428571	0	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #2	6	0	82	2 8	0		0	0	12	0	102	108	6/13/2005	6/19/2005	2005	3	88	52	67.42857	0.78	0.1114	100	41	75.7143	158.6	9.2857	30	76.14285714	92.71428571	0	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #1	176	0	576	6 160	64		0	0	48	0	848	1024	6/20/2005	6/25/2005	2005	4	93	51	72	0.15	0.025	100	32	68,1667	202.3	8.8333	26	84.66666667	92.5	0	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #2	312	8	552	2 144	24		0	0	40	0	768	1080	6/20/2005	6/25/2005	2005	4	93	51	72	0.15	0.025	100	32	68,1667	202.3	8.8333	26	84.66666667	92.5	0	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #1	88	0	(D 80	0		40	0	8	0	488	576	6/26/2005	7/2/2005	2005	5	85	48	66.14286	2.96	0.4229	100	47	80.2857	186.3	11	40	75	97.14285714	22	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #2	48	0	14(D 116	20		4	0	12	0	292	340	6/26/2005	7/2/2005	2005	5	85	48	66.14286	2.96	0.4229	100	47	80.2857	186.3	11	40	75	97.14285714	22	11.194	21.5	33.226	59.3	63,161
GrandFo	k Grand Forks #1	0	1	- 46	6 7	22		38	0	0	0	114	114	7/4/2005	7/10/2005	2005	6	93	48	72.14286	0.17	0.0243	100	49	75.2857	190.1	10.714	33	82.14285714	94.28571429	27	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #2	44	0	216	6 152	96		16	0	12	0	492	536	7/4/2005	7/10/2005	2005	6	93	48	72.14286	0.17	0.0243	100	49	75.2857	190.1	10.714	33	82.14285714	94.28571429	27	11.194	21.5	33.226	59.3	63,161
Grand Fo	k Grand Forks #1	0	0	132	2 32	0		0	0	0	0	164	164	7/11/2005	7/17/2005	2005	7	90	58	74.42857	0.2	0.0286	100	34	70.4286	248.4	7.1429	28	86.14285714	93.28571429	6	11.194	21.5	33.226	59.3	63,161

Subset large dataset into weekly subsets

(week 1 subset shown below)

A A	в	С	D	Е	F	G	н	I	J	К	L	M N	0 F	Q	B	S	Т	U	V	V	Х	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AL	AJ	AK	AL
Countie	s Trap.Location	Male	Anop.heles	Aedes A	Aedes.vexans	Culex	Culex. Tarsalis (Culex.sali	Culiseta O)ther	Total.Fem 1	Fotal.Mosc Week.Start	Week.End Yea	ar Week	: MaxTemp M	1inTemp A	AvgTemp F	Rainfall A	AvgRain N	MaxHumidi I	MinHumid	AvgHumic	WindDir /	AvgWind I	1axWind	MeanMaxTemp	MeanMaxHum a	vgCT	jantemp	ebtemp	narchtemp	apriltemp r	naytemp l	1/1/1/1/1/1/1/1/1/1/1/1/1/1/1/1/1/1/1/	MayRain
Grand F	Fo Grand Forks #1	0	0	0	0	0	0	0	0	0	0	0 5/29/2006	6/2/2006 20	06 1	89	51	70.2857	0.6	0.0857	100	21	68.4286	89.86	7.7143	28	82.57142857	93.7142857	0	28.484	16.25	30.16129	60.367	68.129	3.43	2.4
Grand F	Fo Grand Forks #2	2 0	0	0	0	0	0	0	0	0	0	0 5/29/2006	6/2/2006 20	06 1	89	51	70.2857	0.6	0.0857	100	21	68.4286	89.86	7.7143	28	82.57142857	93.7142857	0	28.484	16.25	30.16129	60.367	68.129	3.43	2.4
Grand F	Fo Grand Forks #1	0	2	25	7	30	17	0	5	1	87	87 5/28/2007	6/4/2007 20	07 1	1 85	42	64.5	0.6	0.075	100	37	72	229.6	11.625	31	76	93.125	12.5	20.387	12.321	35.612903	53.4	69.065	5.7	5.17
Grand F	Fo Grand Forks #2	2 0	0	22	39	3	8	0	0	0	72	72 5/28/2007	6/4/2007 20	07 1	1 85	42	64.5	0.6	0.075	100	37	72	229.6	11.625	31	76	93.125	12.5	20.387	12.321	35.612903	53.4	69.065	5.7	5.17
Grand F	Fo Grand Forks #1	0	0	2	6	0	0	0	0	0	8	8 5/26/2008	6/2/2008 20	08 1	1 82	27	57.125	0.56	0.07	100	18	59.125	131.8	9	26	70.75	85.625	0	13,161	14.931	29.677419	52.3	66.097	1.66	1.06
Grand F	Fo Grand Forks #2	2 0	0	2	0	0	0	0	1	0	3	3 5/26/2008	6/2/2008 20	08 1	82	27	57.125	0.56	0.07	100	18	59.125	131.8	9	26	70.75	85.625	0	13,161	14.931	29.677419	52.3	66.097	1.66	1.06
Grand F	fo Grand Forks #1	0	0	40	0	2	0	0	0	0	42	42 5/25/2009	6/1/2009 20	09 1	79	38	55.875	0.83	0.1038	100	19	67.625	169.5	10.875	33	69.125	93.625	0	10	17.679	29.129032	48.533	63.871	2.7	1.39
Grand F	o Grand Forks #2	20	0	4	0	1	0	0	0	0	5	5 5/25/2009	6/1/2009 20	09 1	79	38	55.875	0.83	0.1038	100	19	67.625	169.5	10.875	33	69.125	93.625	0	10	17.679	29.129032	48.533	63.871	2.7	1.39
Grand F	o Grand Forks #1	0	0	36	7	1	2	0	35	0	81	81 5/31/2010	6/6/2010 20	10 1	78	43	61	0.41	0.0586	100	38	68.1429	269.1	7.5714	26	72.85714286	93.1428571	1	14.806	17.643	39.967742	62.1	66.968	5.95	4.61
Grand F	o Grand Forks #2	20	0	31	0	0	0	0	17	0	48	48 5/31/2010	6/6/2010 20	10 1	1 78	43	61	0.41	0.0586	100	38	68.1429	269.1	7.5714	26	72.85714286	93.1428571	1	14.806	17.643	39.967742	62.1	66.968	5.95	4.61
Grand F	o Grand Forks #1	0	0	0	0	8	0	0	12	0	20	20 5/30/2011	6/5/2011 20	,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,	84	46	62.2857	1.17	0.1671	100	23	66.8571	213.7	13.714	36	72.85714286	86	0	10	18.607	27.645161	50.367	63.903	4.95	2.5
Grandh	o Grand Forks #2	2 U	U	U	U	3	U	U	14	0	1/	17 5/30/2011	6/5/2011 20	лт т 10 г	84	46	62.2857	1.17	0.1671	100	23	66.8571	213.7	13.714	36	72.85714286	86	U	10	18.607	27.645161	50.367	63.903	4.95	2.5
Grandh	o Grand Forks #1	U	U	U	0	0	U	U	0	0	U	0 5/28/2012	6/3/2012 20	12 1	81	33	55.8571	0.12	0.0171	100	25	68.7143	263.3	7.2857	25	68.85714286	94.5714286	0	26.194	29.31	49.354839	58.667	70.581	3.28	1.77
Grandh	o Grand Forks #2	. 0	U	U	U	0	U	U	U	0	U	0 5/28/2012	6/3/2012 20	10 1	0	33	55.8571	0.12	0.01/1	100	25	58.7143	263.3	1.2857	25	00.4005714285	94.5714286	0	26.194	23.31	43.354833	58.667	70.581	3.28	1.00
Grandh	o Grand Forks #1		0	U	0	0	U	0	0	0	0	0 5/27/2013	6/2/2013 20	10 1	1 11	40	60.7143	1.15	0.1643	100	39	13.2857	141.1	11.285	30	63.42857143	92	0	19	13.673	24.935484	33.5	65.871	6.47 C.47	4.83
Grandh	o Grand Forks #2		U	U	0	0	U	0	0	0	0	0 5/27/2013	6/2/2013 20	13 1	1 11	40	50.7143	1.15	0.1643	100	39	13.2857	141.1	7,7140	30	63.42857143	92	0	10,000	13.673	24.935484	33.5	65.871	5.47	4.83
Grandin	O Grand Forks #		0	0	0	0	U	0	0	0	0	0 5/26/2014	0/1/2014 20	14 1	00	51	70.2057	0.6	0.0857	100	21	68.4266 CO.4200	03.00	7.7143	28	02.57142057	33.7142057	0	13.806		27.303226	47.207	65.633	5.3	2.61
Grand f	o Grand Forks #2		0	0	0	0	0	U		0	0	0 5/26/2014	5/1/2014 20 El29/204E 20	14 1	03	00.0	10.2651	0.6	0.0857	0.00	0 122	68.4286 100	03.00	7.7143	20	02.57142057	33.7142857		13.806	14,070	27.303220 43.935494	47.207	65.633 CE E40	5.3	2.01
Grand f	o Grand Forks #	9 10	0	0	35	0	01	NA NA		0	62	71 572572015	5/23/2015 20	15 1	1 75	03.0	85 05	30	62.8	0.66	0.132	100	23	00.0	283.2	10.0	31		22.065	14.673	42.335484	58,367	05.5 lb	5.27	4.47
Grandh	o Grand Forks #2	: 10	U	U	9	14	21	NA	31	3	65	15 5/25/2015	572372015 20	G	15	03.0	85	38	02.8	0.66	0.132	100	23	05.0	203.Z	10.8	31	- 1	22.065	14.673	42.335484	50.367	00.5 lb	5.27	4.47

Trap Count Forecasting Model – PLSR



Fig. 2. Predictor and target variable spaces forming maximal covariant regression

Prediction Results

TABLE I. TABULAR DISPLAY OF DIFFERENT PREDICTION ALGORITHMS COMPARED WITH THE ACTUAL TRAP COUNT FOR 2015 AND THE CORRESPONDING MAE OF EACH PREDICTION. PLSR SHOWS THE LEAST AMOUNT OF PREDICTION ERROR

	2015 Tra	p Count Prediction	n Model Com	parison	
Week	2015 Actual	STL+RandomWalk	Holt-Winters	ARIMA	PLSR
1	1	0	0	0	1
2	1	0	1	0	0
3	3	0	1	13	0
4	3	0	3	0	6
5	3	6	2	6	9
6	2	0	12	13	7
7	8	1	16	13	12
8	16	26	16	9	12
9	15	8	2	18	15
10	25	40	15	16	32
MAE		5.62	4.5	5.3	3.3



WNV Human Cases Binomial Prediction Modeling

Using binomial prediction methods, Random Forest, Regression tree, logistic regression

Predict based on meteorological variables and trap count whether WNV will be contracted by a human

	RandomForest		Error
Actual	0	1	
0	260	0	0
1	2	8	0.2

Random Forest Prediction confusion matrix results

Risk Maps Website – Google Fusion Tables

Fig. 4. Layered Google Map Showing Culex Tarsalis in colored layers and a pop up box displaying Grand Forks County information

WEBSITE

Fig. 3. Layered Google Map displaying colors that correspond to mosquito trap counts. Red counties indicate high population, green indicate low. Red markers correspond to actual trap locations in North Dakota. This type of map will be used to show trap counts and WNV risk

Future Work

- Train student or department to do modeling
- Improve Accuracy of Culex tarsalis trap count model
- Continued development and accuracy improvement of human WNV contraction model
 - Further analysis of Minimum Infection Rate (MIR) data
 - Vector Index (VI)
- Extend the scope of prediction models to all counties
- Collection and addition of key weather variables to website analysis interface

Publications

M. Campion, C. Bina, **P. Ranganathan** et.al. Predicting West Nile Virus (WNV) Occurrences in North Dakota using Data Mining Techniques FTC 2016 - Future Technologies Conference 2016, 6-7 December 2016 | San Francisco, United States.

Planning to submit new additional findings to "Journal of Entomology"

FTC 2016 - Future Technologies Conference 2016 6-7 December 2016 | San Francisco, United States

Predicting West Nile Virus (WNV) Occurrences in North Dakota using Data Mining Techniques

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