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MODELING NITROGEN LOADING RATE TO DELAWARE LAKES USING REGRESSION AND NEURAL NETWORKS

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ABSTRACT

The objective of this research was to predict the nitrogen-loading rate to Delaware lakes and streams using regression analysis and neural networks. Both models relate nitrogen-loading rate to cropland, soil type and presence of broiler production. Dummy variables were used to represent soil type and the presence of broiler production at a watershed. Data collected by Ritter & Harris (1984) was used in this research. To build the regression model Statistical Analysis System (SAS) was used. NeuroShell Easy Predictor, neural network software was used to develop the neural network model. Model adequacy was established by statistical techniques.

A comparison of the regression and neural network models showed that both perform equally well. Cropland was the only significant variable that had any influence on the nitrogen-loading rate according to both the models.

INTRODUCTION

Delaware lakes and streams have experienced a significant environmental degradation over the past several decades due to various human activities such as fertilizer and manure application. These activities lead to elevated concentrations of nitrogen in lakes and streams.

Nitrogen is among the most abundant elements found in our atmosphere. Nitrogen may exist in the free state as gas N_2, nitrate, nitrite or ammonia. Nitrogen containing compounds act as nutrients in streams and rivers. Nitrate does not cause health problems until reduced to nitrite. Nitrites can produce serious condition in fish called " brown blood disease." Nitrites also react directly with hemoglobin in human blood and other warm-blooded animals to produce methemoglobinemia and can cause a condition called methemoglobinemia or "blue baby disease." The effective management of the factors affecting water quality in lakes and streams is extremely critical for the existence of the aquatic species and for maintaining acceptable water quality for humans.

Ritter and Harris (1984) sampled sixty-two watersheds and thirty lakes in Delaware for a period of one year from March 1979 to March 1980 and estimated the nitrogen loading rates for each of the sampled lakes and watersheds. In their research they stated that baseflow transported greater percentage of nitrogen as opposed to stormflow. Well-drained soil had higher nitrogen loading rates and watersheds with greater drainage area in cropland had the highest nitrogen loading rates.

The objective of this research was to model nitrogen-loading rate to Delaware lakes and streams using the data collected by Ritter and Harris using regression analysis and neural network. A comparison of both models was made to see if both the models performed equally well and gave similar results.

LITERATURE REVIEW

The increase in nitrogen loading has led to a number of problems. There has been an increase in the level of nitrogen in drinking water. The high level of nitrate concentration in water makes it necessary to use expensive purification systems in the best interests of human health.

Urban uses of fertilizers, manure used in agriculture and combustion of fossil fuel are some of the human activities which contribute significantly towards the increase in the nitrogen loading rate in lakes and streams. Local and regional environmental characteristics and seasonal effects also affect the nitrogen-loading rate.

High concentration of nitrogen in agricultural streams is due to the fertilizers and manure used for crops and from livestock wastes. High nitrogen level in urban streams is due to the pollution from automobiles, electric power plants among many others.

Nutrient conditions differ by land use. In areas of mixed land use the nutrient concentration is lower as opposed to agricultural or urban areas but is higher in comparison to undeveloped areas and forests. Nutrient conditions in streams are generally higher than those in shallow groundwater regardless of the land use except for in agricultural areas.

The Center for Inland Bays in Lewes, Delaware, developed a model to quantify the nitrogen loading using GIS analysis. Loading rates for each land use were based on monitored data and literature values for similar land uses where no actual data were available. They used local measurements of nitrogen concentrations in groundwater below agricultural areas to refine the loading estimates for fertilizer applications. According to their study, the majority of nitrogen is contributed by manure and agricultural fertilizers applied to the crops which support the region's poultry industry. The second main source found was residential development, which relies mainly on on-site wastewater disposal systems. Their results of nitrogen modeling showed that the loadings of the entire system were twice the overall carrying capacity.[1]

Since 1972, when the Federal Water Pollution Control Act was passed, many water quality management projects have been initiated. Nonpoint sources of pollution have been given a lot of attention. Agricultural practices and the extent to which they affect this kind of water pollution have been under study since.

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[1] The carrying capacity is the ability of a waterbody to assimilate nitrogen before there are adverse impacts.

Thomas and Crutchfield (1974) sampled eight streams draining the agricultural watersheds in the important physiographic regions of Kentucky. The sampling was done from January to May of 1971 and 1972. The object of their study was to determine the effects of geology and land use on the nitrate-N and P concentrations in the stream water. According to their results, the nitrate content in the streams varied from month to month. Barisas *et al.* (1978) examined the effects of different tillage practices on nitrogen losses in runoff and sediment from experimental plots using simulated rainfall and found that the nitrogen losses had no correlation with percent crop residue.

According to Humenik *et al.* (1978), the streams draining different physiographic regions in North Carolina were found to have very little difference in average nitrogen concentrations. In another study done by Barker, Felton and Cohen (2002) percent agriculture in the site's catchment showed a strong relationship to the amount of instream nitrate.

Under section 314 of the Clean Water Act, the Delaware Division of Fish and Wildlife received a grant in March 1979 to survey and classify the 30 publicly owned lakes in Delaware according to their trophic conditions and to establish which lakes needed restoration. The Department of Agricultural Engineering, University of Delaware conducted the survey for the Division of Fish and Wildlife (Ritter *et al.,* 1980; Ritter 1981).

Ritter and Harris built a model using stepwise multiple regression. They sampled 62 watersheds and thirty lakes for one year. Each lake and watershed was assessed for nitrogen loads. It was found that the nitrogen loads varied from 8.0 to 38.5 kg ha^{-1} yr^{-1}. A higher percentage of nitrogen was transported in baseflow than stormflow. It was also found that the soil type and percentage cropland had an effect on the nitrogen-loading rate. Soil type was classified into three categories: extremely well drained, well drained and poorly drained. Extremely well drained soil was found to have higher nitrogen loading rates as opposed to poorly drained. The watersheds that had higher percentage of drainage in cropland had the highest nitrogen-loading rate. Broiler production did not have a large impact on the nitrogen-loading rate.

Ritter and Harris in their research built the model using stepwise multiple regression technique. This research uses the data collected by Ritter and Harris and models nitrogen-loading rate to Delaware lakes and streams using multiple regression analysis and neural network techniques.

DATA

Data collected by Ritter and Harris from March 1979 to March 1980 was used for this research. A total of 30 lakes ranging from 7 to 77 ha were sampled nine times under base flow conditions during the period. All tributaries and lake outflows and two or three points in each lake were sampled. A total of 62 tributaries were sampled. Grab samples were also taken from some of the tributaries and lake outflows during storm events.

When all the baseflow and stormflow samples were taken their flow measurements were also taken. All samples were analyzed for ammonium nitrogen, nitrate – nitrite nitrogen and organic nitrogen. Stream distillation and nesslerization was used for analyzing ammonium nitrogen. Devarda's alloy reduction method (APHA, 1975) was used for analysis of nitrate-nitrite nitrogen and micro Kjeldahl and nesslerization (APHA, 1975) was used for the analysis of organic nitrogen. Normalized monthly flow rates were estimated for all tributaries of all lakes from USGS gauging station records. Nitrogen non-point source loads were calculated on a monthly basis and added together to estimate the annual loads given in the report.

One data point was not representative of the population and was not used in this research. Turkey Branch had fairly extensive broiler production and showed a high nitrogen-loading rate of 38.5 kg ha^{-1} yr^{-1} for only 36.7% cropland. This point was clearly an outlier and was hence, not used.

Drainage area, land use and major soil types were determined for all tributaries. Drainage areas were determined from USGS topographic maps while land use was measured from land-use maps prepared by the Delaware State Planning Office in1973. Major soil types were determined from soil survey maps.

Methodology

In order to model nitrogen-loading rate to Delaware lakes and streams regression analysis and neural network techniques were employed. Model adequacy was established for both the models. Model validation was further performed on regression and neural networks model and in the end a comparison of both models was made.

REGRESSION MODEL

Based on nitrogen loading theory, nitrogen-loading rates are affected by land type (cropland, forest, urban), soil type (well-drained, poorly drained), presence of broiler production, seasons and rainfall (data for the variable seasons and rainfall was not available and was therefore not used in this study). Land type, forest was not used in the model to remove perfect collinearity as all three land types add up to a 100% land type. The economic model is:

NLR = $\boldsymbol{f}$ (cropland, cropsq, urban, soil, broiler).

Nitrogen-loading rate increases with the increase of agricultural practice. Quite a few independent variables take the value zero as can be seen from the observations (Table 5). Also the values for nitrogen loading rate were not very large. As a result the Level-Level linear model was used to build the relationship of the nitrogen-loading rate. The regression model can be expressed as:

$NLR = b_0 + b_1 cropland + b_2 cropsq + b_3 urban + b_4 soil + b_5 broiler + e$

Where:

NLR: is the nitrogen-loading rate measured in kg ha^{-1} yr^{-1}. It is the dependent variable.

cropland: is the percentage of cropland in the total land area.

cropsq: is the square of percentage of cropland in the total land area.

urban: is the percentage of urban land type in the total land area.

soil: is the soil type. It is a dummy variable. If it is well drained then it takes the value 1, else takes value 0 (poorly drained).

broiler: represents if broiler production is present at the given watershed or not. Takes value 1 if it is present, else takes value 0.

Hypothesis: $b_1 > 0$, $b_2 < 0$, $b_3 > 0$, $b_4 > 0$, $b_5 > 0$, as intuition and literature says that the presence of these variables should increase the nitrogen loading rate.

In this model, 49 data points were used for training and 12 data points were used for validation. The SAS program (SAS, 1990) was used for generating the regression model. Regression diagnostics as discussed here were examined for evaluating model adequacy and regression assumptions. The diagnostic methods use both statistical techniques and visual inspection techniques. White's test was used for testing for heteroscedasticity. The residual plots against cropland and nitrogen-loading rate used are very effective in detecting abnormal behavior of the residuals.

The model adequacy is established by the fact that the values of R^2 and F are high, the t-values of the regression coefficients are all significantly different from zero, the signs of the coefficients are all correct, and the assumptions dealing with linearity, uniform scatter, independence and normality of errors are supported.

REGRESSION RESULTS AND DISCUSSION

Regression results are summarized in Table 1 and Table 2. The regression equation for the predicted loading rate is as follows:

$$NLR = -6.77461 + 0.54435\ cropland - 0.00269\ \text{cropsq} + 0.14423\ urban + 0.17250\ soil + 3.29500\ broiler$$

As observed from Table 1, $R^2 = 0.3510$. R^2 measures the proportion of variation in the dependent variable explained jointly by the independent variables.

The F-value for testing the overall significance of the model is 4.65 and the p-value (minimum level of significance for rejecting the null hypothesis) is 0.0018 which is less than $\alpha = 0.05$. This suggests the model is significant.

The chi-square statistic for heteroscedasticity is 22.52 and the p-value is 0.1654 > 0.05, therefore, we fail to reject the null hypothesis that there is no heteroskedasticity.

Table 2 shows p-value for the independent variable *cropland* is 0.0405 < 0.05. This implies that *cropland* is the only significant coefficient**.** The coefficient for *cropland* is 0.54435 > 0, indicating that increase in *cropland* leads to increase in nitrogen loading rate.

The Variance Inflation Factor values for independent variables, *cropland* and *cropsq* are > 10 and the condition index value for the independent variable *broiler* is > 30, which are rules of thumb for checking for multicollinearity. Following these rules we find that the model has multicollinearity. However, this was expected given the form of the model and not viewed as a reason for concern towards the result.

A t-test was performed to confirm that the observed data (Table 5) does not differ significantly from the trained data (Table 6). The null hypothesis H_0 for this test is that there is no significant difference between the observed and the trained data.

The null hypothesis is rejected if at the given 5% significance level, p-value of the calculated t-value is less than the 0.05. Rejection of the null hypothesis would mean that the trained data are not from the same population as the actual data. R^2 value would determine the closeness of fit.

With the help of spreadsheet software the p-value of the calculated t-value was = 1 which is > 0.05. Hence, we fail to reject the null hypothesis. This implies that the trained data are in accordance with the observed data.

In order to check the misspecification and regression assumptions, the residuals scatter plot, shown in *Fig. 1*, is used. The residuals randomly scatter around zero and show no discernable pattern in the residual scatter plot against the loading rate.

NEURAL NETWORK MODEL

NeuroShell Easy Predictor (Ward Systems Group, Inc., 1997) was chosen to formulate a neural network model for nitrogen loading rate. Genetic algorithms were applied to this model. NeuroShell Easy Predictor is a software program designed to simplify the creation of a neural network application to solve prediction and pattern recognition problems. Bauer (1993) defined genetic algorithms as software procedures modeled after genetics and evolution.

In genetic algorithm the idea of survival of the fittest has great importance. Genetic algorithms make use of a fitness function to select the fittest string that will be used to create new and better population strings. The fitness function takes a string and assigns a relative fitness value to it. These fitness values are then used to select the fittest strings.

Neural network technology is based on the brain's problem solving process. Humans use knowledge gained from past experiences for new situations. Similarly, a neural network takes previously solved examples to build a system of neurons that solve the problem. Just like a biological neuron, each processing element may receive many inputs but will compute a single output. Chitra (1992) described a model of neurons in the following manner:

(1) Inputs X_i assigned weights W_i are received from other neurons (i = 1, 2, …n).
(2) The product of inputs and weights are summed by the neuron which then add the node bias.
(3) Functions like threshold and sigmoid transform the calculated sum.
(4) The output Y is sent to the other neurons.

The values of weights represent the state of knowledge of the neural network. Eighty percent of the data is used for training. The trained neural network can then be used for the remaining 20% data for prediction.

In this model, 49 data points were used for training the network and 12 data points were used for validation. The data was divided into two parts – input columns and output column. Five input columns were used for the independent variables *cropland, cropsq,* *urban* and the dummy variables *soil* and *broiler*. The output column was nitrogen-loading rate *(NLR)*.

NEURAL NETWORK MODEL RESULTS AND DISCUSSIONS

Fig. 2 shows the graph showing the relative importance of the inputs cropland, soil and broiler according to the neural network model. As can be seen from the figure cropland was the most significant variable.

A t-test was performed to confirm that the observed data does not differ significantly from the trained data. The null hypothesis H_0 for this test is that there is no significant difference between the observed and the trained data.

The null hypothesis is rejected if at the given 5% significance level critical t-value is greater than the t value from the table. Rejection of the null hypothesis would mean that the trained data are not from the same population as the actual data. R^2 value would determine the closeness of fit.

With the help of spreadsheet software the p-value of the calculated t-value was =0.9742 which is > 0.05. Hence, we fail to reject the null hypothesis. This implies that the neural network trained data are in accordance with the observed data. R^2 was 0.4111.

In order to check the misspecification the residuals scatter plot, shown in *Fig. 3*, is used. The residuals randomly scatter around zero and show no discernable pattern in the residual scatter plot against the loading rate.

COMPARISON OF REGRESSION AND NEURAL NETWORK MODELS

The results of regression model found cropland significant. Cropland was also the main important factor in the neural network model.

To compare the accuracy of the two models, mean absolute error (M.A.E.), an error statistic was used. Moreover, a t-statistic for testing paired difference was performed. The t-value was used to confirm whether there is significant difference between the regression model and the neural network model. The null hypothesis H_0 for this test was that the mean difference of the performance, $\bar{d}$, is not significantly different from 0. The t-value was computed using the following formula:

$$t=\bar{d}/S_d$$

where S_d is the sample standard deviation of $\bar{d}$. The null hypothesis is rejected if the significance level of the t-value is less than $\alpha = 0.05$.

MAE from the regression model, 3.9993, was slightly smaller than from that of the neural network model, 4.1780. Table 3 and Table 4 show the comparison of the actual and predicted values for regression model and neural network model, respectively.

The probability of calculated t-value is $1.4142 > \alpha = 0.05$. Hence, we fail to reject the null hypothesis. Thus, the mean difference of the performance is not significantly different from 0. Hence we conclude that both models perform equally well.

MODEL VALIDATION

The most effective method of validating the model is to use data that are not used in model building or training. Mean Absolute Error (MAE) and Mean sum of squared error (MSS) was used to compare the model's performance on validation data sets. The calculated values are shown in Tables 3 and 4. The difference in the performance of the trained and validation data models was not significant.

CONCLUSIONS

The level-level linear regression model can be used to formulate model of nitrogen loading rate from the observed data. The model is adequate for predicting the nitrogen-loading rate because of the significance of the F, t and χ^2 statistics. The visual inspection of the residual plots confirms the adequacy of the model. Cropland is the only independent variable that is significant and has a positive effect on nitrogen loading rate. The low value of F and low R^2 may be because of limitations such as missing important variables such as rainfall data or due to other measurement errors.

The value of R^2 and the significance of the t-statistics confirm the adequacy of the neural network model, which was constructed using NeuroShell Easy Predictor. The comparison of regression and neural network model shows that both perform equally well. We thus conclude that both regression and neural network models are adequate models for predicting the nitrogen loading rates for Delaware lakes and streams.

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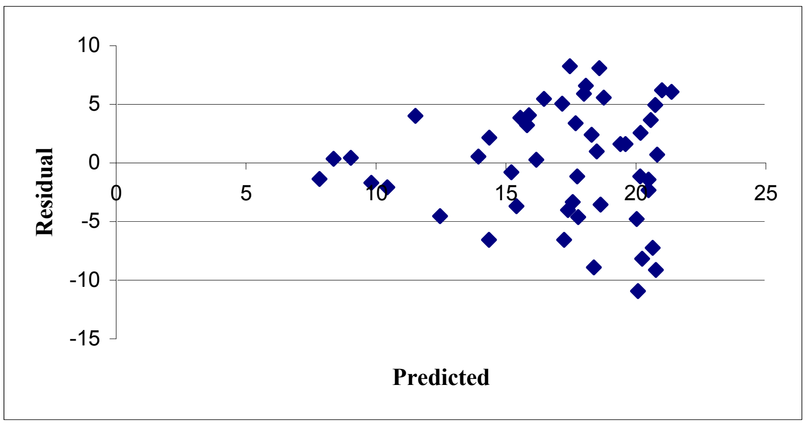
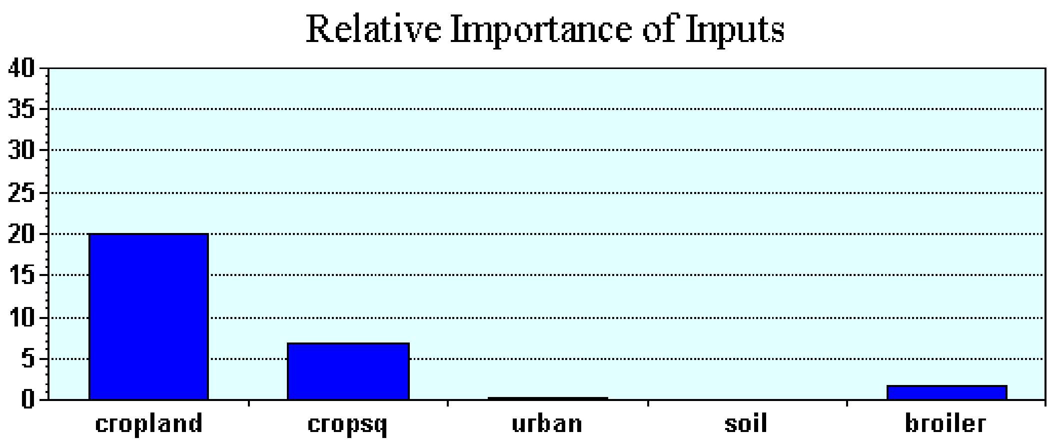
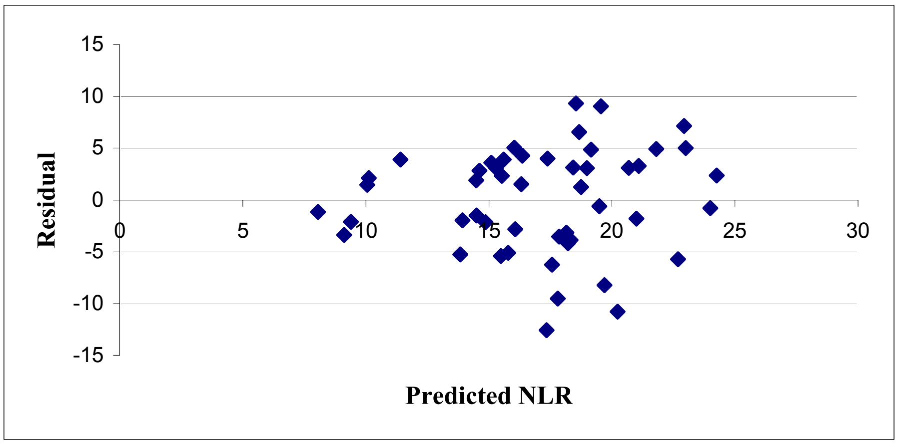


Residual Vs. Predicted NLR (Regression Model)
Fig.1



(19.92%) (6.75%) (0.16%) (0%) (1.57%)

Fig.2



Residual Vs. Predicted NLR (Neural Network Model)
Fig.3

Table 1

Regression output for fitted model

Dependent variable	NLR
Observations	49
R^2	0.3510
Root mean square error	5.1269
Overall testing for F	4.65
Significance level of F	0.0018
Specification of χ^2	22.52
Significance level of χ^2	0.1654

Table 2

Fitted regression model coefficients

Variable	Coefficient	Standard error	*t*-value	Significance
Intercept	-6.77461	8.25775	-0.82	0.4165
cropland	0.54435	0.25776	2.11	0.0405 *
cropsq	-0.00269	0.00194	-1.39	0.1729
urban	0.14423	0.09970	1.45	0.1552
soil	0.17250	3.14824	0.05	0.9566
broiler	3.29500	2.60815	1.26	0.2133

* Significant at 5% level

TABLE 3

Validation of Regression Model

	Training data	Validation data
MAE	3.9993	4.3380
MSS (error)	12.4732	14.8588
Accuracy[2]	74.9209%	76.6683%

TABLE 4

Validation of Neural Network Model

	Training data	Validation data
MAE	4.1780	4.1697
MSS (error)	14.6112	22.9426
Accuracy	73.7081 %	75.8099%

[2] Accuracy = 100-%error, where %error = 100*(abs (predicted value-actual value)/actual value))

Table 5
Training Data Set

NLR(actual)	cropland	urban	soil	broiler
20.9	50.9	1	w	yes
21.3	68.8	14.2	w	no
14.8	96.7	0.8	w	no
15.8	88.3	1.8	w	no
11.5	57.9	15.1	w	no
10.5	66.3	6.4	w	no
13.2	55	1.9	w	yes
13.4	50.2	0	w	no
12.6	56.1	2.4	w	no
11.8	56.3	2.5	w	no
17.6	74.9	7.6	w	no
15.9	66.2	4.5	w	no
20.1	74	13	w	no
15.3	93.8	4	w	no
7.5	32	2.3	p	yes
11	45.3	4.4	w	yes
21.4	63.1	2.4	w	no
24.8	82.8	0	w	no
20.9	49.7	3.7	w	no
17.8	75.6	1.6	w	no
18	78.1	0.7	w	no
14.3	66.4	0	w	no

16.9	89.5	0	w	no
27.9	88.5	1	w	no
16	43	0.6	w	yes
29.9	62.9	3.3	w	yes
11.5	27.9	0.2	w	yes
23.8	63	1.5	w	no
22.8	88.5	1.1	p	no
12.1	59.7	5.9	w	no
12.1	62.8	7.1	w	no
22.2	65.6	7.7	w	no
22.4	64.6	3.1	w	no
27.3	65.1	6.6	w	no
28.4	84.1	0.6	w	no
21.9	81	4.5	w	no
12.5	30	0	p	yes
12.2	40.5	0.2	w	yes
18.9	51.7	0.7	w	yes
9.2	62	4.5	w	no
15.9	56.5	4.2	w	no
9.2	0	100	w	no
8	24.8	0	p	yes
8.6	26	0	w	yes
11.7	44.2	0.4	w	yes
31	78.6	3.6	w	no
17.5	68.4	3.1	w	no
19.1	43.2	1.5	w	yes
17	44	2.2	w	no

Table 6
Validation Data Set

NLR(actual)	cropland	urban	soil	broiler
19	82.4	0	w	no
18.2	54	0	w	no
27.2	80.2	0	w	no
18	42.6	1.2	w	yes
19.1	73.9	0.8	w	no
16.5	39.8	5.6	p	yes
29.2	70.9	0	w	no
27.5	80.9	1.1	w	no
17.7	50	1.2	w	yes
11.9	16.7	67.7	w	no
8.9	50.8	0	w	yes
21.7	48.3	0.3	w	no

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