PREDICTION OF INCIDENCE AND SEVERITY OF COFFEE LEAF RUST

A Project Report

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Master of Management

By

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I would forever be indebted to my parents for their blessings that saw me through all the difficult times.

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IISc, Bangalore

25/06/2018

Abstract

Coffee leaf rust is a disease caused by the fungus, Hemileia Vastatrix. It leads to premature fall of leaves and leads to huge losses of yield. In recent years there have been outbreaks around the world especially Latin America. Indian coffee plantations also suffer from coffee leaf rust and the disease outbreaks have been commonplace in recent years.

Prediction of the disease incidence in advance can be very helpful in alerting farmers and can ultimately decrease the losses of yield and reduce cost of combatting the disease. There has been an increasing number of research papers focused on prediction of coffee leaf rust incidence and severity using machine learning methods. [3] In this project, coffee leaf rust disease variables and weather variables have been modelled using vector Autoregression (VAR) and forecasting of coffee leaf rust has been done. The motivation behind using VAR comes from the field of econometrics where it has been used widely for modelling multiple time series variables and to understand the relationship among the variables. The same has been investigated in this study, through structural analysis.

Later in the project, recurrent neural network and one of its most popular variant, LSTM has been used for modelling the rust incidence and severity. The forecast from VAR and LSTM has been compared. Finally, a model for forecasting leaf rust incidence has been proposed in the conclusion.

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Chapter One

Introduction:

Background:

Coffee leaf rust is one of the most important disease of coffee leaves. This disease can be very devastating for a coffee plantation and can reduce yields considerably. The arrival of the disease also leads to increased cost of combatting the disease. So, economically it is one of the most important diseases on coffee plants.

Coffee rust epidemics, with intensities higher than previously observed, have affected several countries in recent years including: Colombia, from 2008 to 2011; Central America and Mexico, in 2012–13; and Peru and Ecuador in 2013 [2]. There has been an increasing number of research papers focused on prediction of coffee leaf rust incidence and severity using machine learning methods, presumably because of coffee leaf rust epidemics becoming more common and advances in machine learning and deep learning. The accuracy of models predicting disease has not been up to the mark [7].

Many of the literature on prediction of coffee leaf rust incidence and the severity of the disease suggest that machine learning techniques have been used extensively for the same [3]. Impacts of coffee leaf rust are devastating and leads to premature fall of leaves which decreases yield considerably. It also leads to increased cost of controlling and combatting the disease [4].

Problem statement:

An experimental trial was initiated in one of the CCRI farms in Karnataka, India, to record the leaf rust incidence on S.795, Sln.5B and CXR varieties for developing forewarning model on the outbreak of diseases. Observations on leaf rust disease were recorded on fortnightly basis from S.795 Sln.5B and CXR. In all three varieties, twenty-five plants have been marked and observations were recorded on total number of plant population infected, incidence of leaf rust and its severity. A forewarning model of leaf rust incidence and severity must be developed for the plantation so that the owners can take appropriate measures to prevent the outbreak of the disease.

Literature review:

There have been many research papers focusing on predicting coffee leaf rust incidence and severity using machine learning algorithms. David Camillo Corrales et. al. in Two-Level Classifier Ensembles for Coffee Rust Estimation in Colombian Crops proposed classifier ensembles of Neural networks, regression tree and support vector regression for coffee rust estimation. The dataset used was composed of three categories, namely, weather conditions (six attributes), physic crop properties (three attributes) and crop management (four attributes). Perez Ariza et. al. [1] presented an agricultural case study for prediction of coffee leaf rust using Bayesian networks. The dataset comprised of monthly accounts of coffee leaf rust incidence. In the paper Using nondeterministic learners to alert on coffee rust disease **-** Oscar Luaces et. al. discretized the continuous the disease variable and predicted if it will be greater than a given threshold. The dataset comprised of monthly accounts of coffee leaf rust incidence in an experimental farm in Brazil.

In this work I have used Vector Autoregression (VAR) which is one of the most commonly used methods in time series forecasting for multivariate time series, especially in econometrics. Later in the project I have used long short-term memory (LSTM), a type of RNN. LSTM has been very successful on different sequence learning tasks such as natural language translation, speech recognition, time series forecasting. Both of the techniques have not been used for prediction of coffee leaf rust in previous works.

Flow of project report:

In chapter two I have described the data collection methodology and a brief discussion of the data set has been done. In this work, Vector Autoregressive (VAR) models have been used to model incidence (percentage of coffee leaves infected out of the total observed) and severity (the average intensity of the rust) of coffee leaf rust along with five weather variables. Vector autoregressive models (VAR) are used to model multiple time series and the two main goals of VAR are forecasting and structural analysis [5]. The same has been discussed in chapter three. It has been shown in previous research that there is a link between the weather conditions and the intensity of disease [6]. Structural analysis has been done to discover Granger causality among the weather and disease variables, instantaneous causality. Impulse response analysis has been done to explore the affects of giving a unit shock in one of the weather variables induces the disease variables to change and how. In chapter 4 recurrent neural networks have been introduced. Chapter 5 deals with the comparison of the accuracy of VAR and LSTM models. Finally, conclusion and references are attached at the last.

Chapter Two
Data collection, description

Data collection

Data was collected on an experimental farm having the below illustrated setup:

An experimental trial was initiated in the CCRI farm to record the leaf rust incidence on S.795, Sln.5B and CXR varieties for developing forewarning model on the outbreak of diseases. Observations on leaf rust disease were recorded at fortnightly interval from S.795 Sln.5B and CXR for a span of eight years.

In both Arabica and Robusta cultivars twenty-five plants have been marked and observations were recorded on total number of plant population infected, incidence and severity of the leaf rust.

Procedure followed for recording the observations: All the standard recommended practices applied to the experimental blocks. For leaf rust studies, use of systemic fungicides in Arabica plots was avoided. In each of the experimental plots, five spots were marked in the below manner.

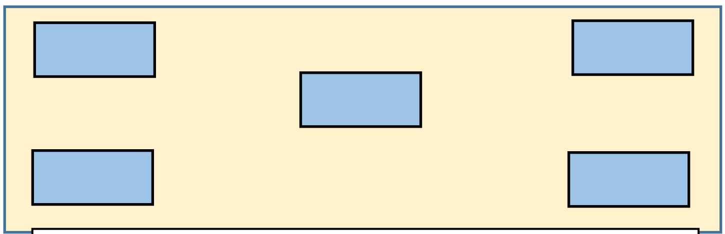


Fig- 2.1 – A plot showing the experimental farm

In each spot five normal plants were marked randomly, for recording of various observations by Agronomists, Entomologists and Plant Pathologists.

Two categories of data were collected for the plantation:

a) Weather variables
b) Rust measures

Five weather variables were collected monthly and they are:

a) Average maximum temperature (monthly)
b) Average minimum temperature(monthly)
c) Average Relative humidity(monthly)
d) Average Rainfall
e) Average Sunshine

Three measures for leaf rust were collected fortnightly:

a) Population infected
b) Rust incidence
c) Severity

a) Population infected: (Number of plants infected/Total number of plants observed) *100

b) Rust incidence: (Number of infected leaves/Total number of leaves observed) *100

c) Severity: (Sum of severity ratings of all observed leaves/ (5* Total number of leaves observed))*100

Population infected measures the percentage of plants that have been infected out of total observed. Rust incidence measures the percentage of leaves infected out of the total number of leaves observed. The two measures are only giving information about how much of the population is infected by the rust incidence. Severity measures the intensity of the rust. Every leaf is given a rating based on the infection and then the ratings are added up and then divided by five times the number of leaves observed. The whole quantity is multiplied by 100 so that the range of the severity is between 0 to 100.

Chapter 3

VAR modelling

For this project I have a total of eight time series variables. Five of them are weather variables and three are disease variables. When there are a lot of variables then it is also often of interest to learn about the dynamic interrelationships between several variables. VAR is used to model multivariate time series and provides great interpretation tools that improve the understanding of the dynamic interrelationships among the time series variables. In particular, Granger causality leads to infer about the causal relationships among variables.

For instance, in a system consisting of three disease variables and five weather variables, one may want to know about the likely impact of a change in one of the weather variables, let's say average minimum temperature, on one of the disease variables, for instance rust incidence. The interesting questions that demand an answer could be: What will be the present and future implications of such an event for rust incidence? Under what conditions can the effect of an increase in average minimum temperature be isolated and traced through the system? These questions can be answered through structural analysis using VAR. But equally important objective of VAR is forecasting. The two main goals of using VAR are forecasting and structural analysis [5].

VAR Model:

VAR models are the state-of-the-art when it comes to modelling multiple time series variables. A VAR model describes the evolution of a set of *k* variables (called *endogenous variables*) over time (sample period) as a linear function of only their past values. The variables are modelled as a linear combination of their own lagged values and of lagged values all other variables in the system.

For illustration a VAR(p) model:

VAR(p) model:

$$y_t = \nu + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t$$

where, $y_t = (y_{1t} \dots y_{kt})'$ is a $K * 1$ random vector, the A_i are fixed $K * K$ coefficient matrices, $\nu = (\nu_1, \dots \nu_k)'$ is a fixed $K * 1$ vector of intercept terms allowing for the possibility of non-zero mean term, $E(y_t)$. $u = (u_{1t} \dots u_{kt})'$ is a K-dimensional white noise or innovation process, that is, $E(u_t) = 0$, $E(u_t u_t')$ = $\sum_u$ and $E(u_t u_s') = 0$ for $s \neq t$. The covariance matrix is assumed to be non-singular.

One of the parameters of VAR model is the number of lags, which determines the number of past lags that will be used to model variables as linear combination of past lags of itself and all other variables. The order of VAR model is identified based on various criteria such as AIC, SC, HQ and FPE.

It is very difficult to interpret the coefficients of the variables. Another interpretation tool for VAR is the covariance matrix of the residuals. For a VAR system with eight variables the covariance matrix will be 8*8 or will have 64 terms out of which there will be (64 – 8)/2 = 28 covariance terms. If we want to only look at the covariances then also we will have to interpret 28 covariance terms which is a difficult task.

'Structural VAR' is a depiction of the underlying "structural" relationships between the variables under consideration.

Two features of the structural form that make it the preferred candidate to represent the underlying relations are:

1) Make the residuals uncorrelated
2) Presence of contemporaneous impact between variables

Modelling procedure:

VAR order:

To select the VAR order for the system I used Scwartz criteria. It gave the VAR order to be 1.

Model, plots and interpretation:

Weather variables:

The dataset comprises of average monthly accounts of maximum temperature, average minimum temperature, Sunshine, rainfall and relative humidity. Let's have a look at the time series plots of the weather variables.

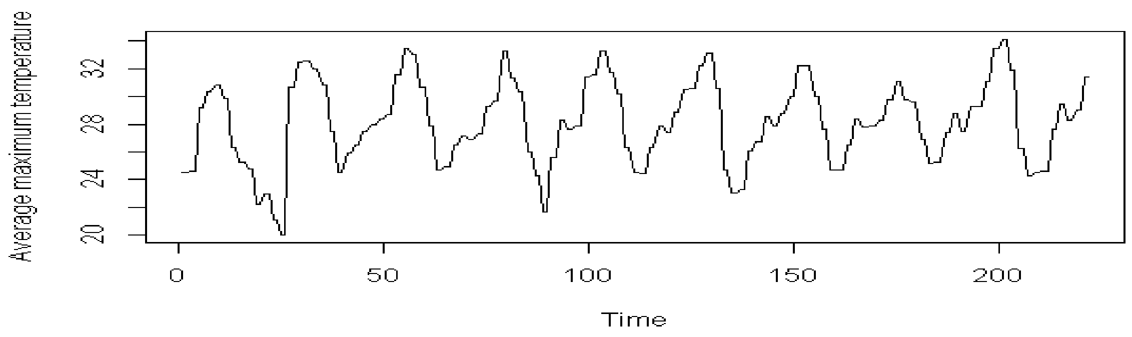


Fig- 3.1 – A time series plot showing the average max temperature

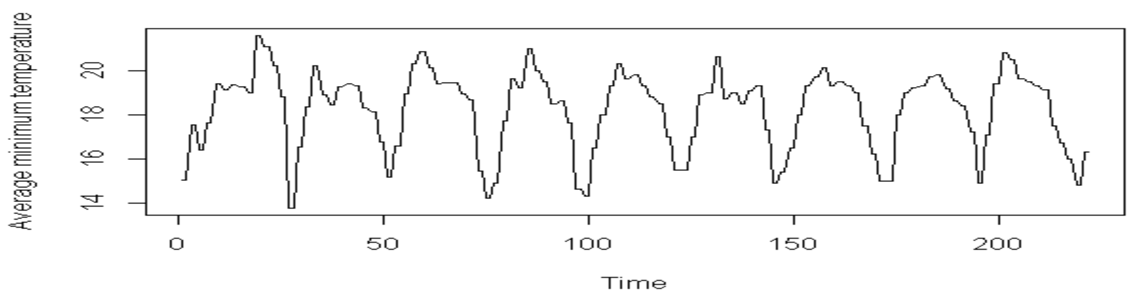


Fig- 3.2 – A time series plot showing the average min temperature

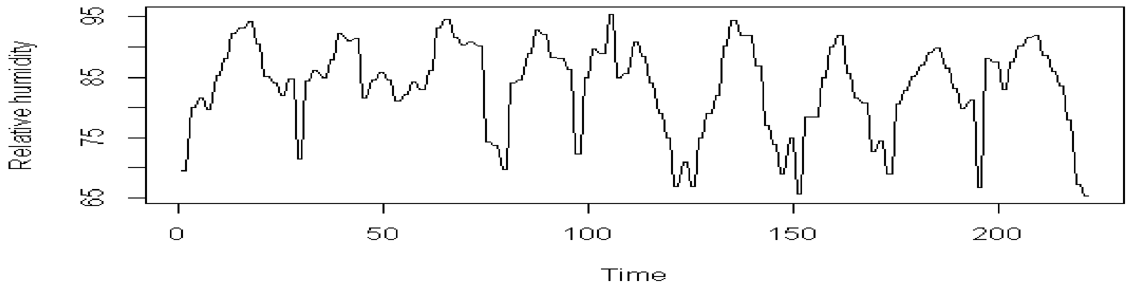


Fig- 3.3 – A time series plot showing the relative humidity

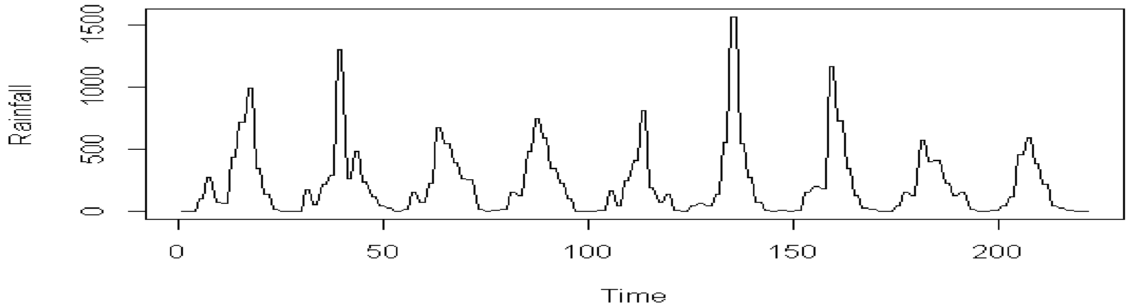


Fig- 3.4 – A time series plot showing rainfall

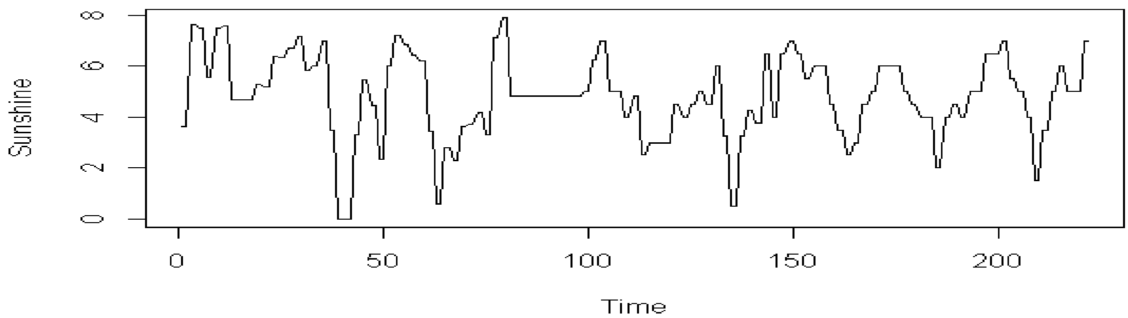


Fig- 3.5 – A time series plot showing sunshine

Coffee varieties:

We had total of three coffee varieties to model. They were:

a) S795
b) Sln5B

c) CXR

For each variety three disease variables were recorded fortnightly over a span of eight years on the experimental farm. Two of the three disease variables are the main variables of interest and they are:

a) Rust incidence: This depicts the percentage of leaves infected out of the total number of leaves observed.
b) Severity: This measure depicts the average intensity of the infection over the observed samples.

Modelling S795:

Rust incidence:

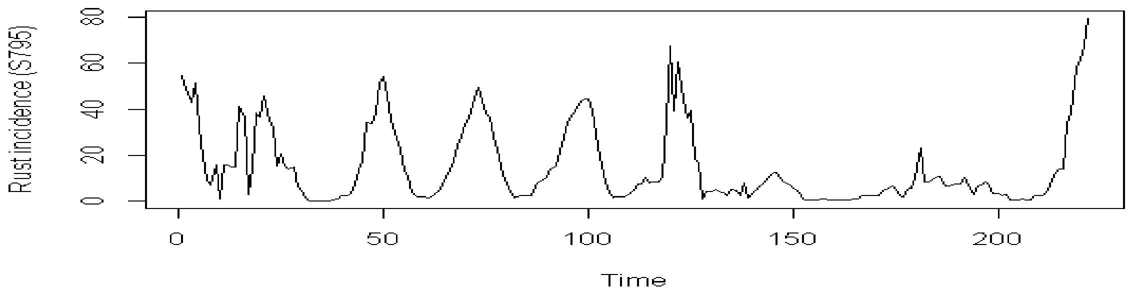


Fig- 3.6 – A time series plot of Rust incidence of S795

The optimal order of the model found to be was 1 using AIC, Scwartz criteria. The final model with the significant terms are:

```
Estimation results for equation RustIncidence:
==============================================
RustIncidence = Sunshine.l1 + RustIncidence.l1 + const

                 Estimate Std. Error t value Pr(>|t|)
Sunshine.l1      -0.88410    0.30628  -2.887  0.00433 **
RustIncidence.l1  0.86729    0.03272  26.503  < 2e-16 ***
const             5.86856    1.61280   3.639  0.00035 ***
```

The only significant terms are sunshine at lag 1 and rust incidence at lag 1.

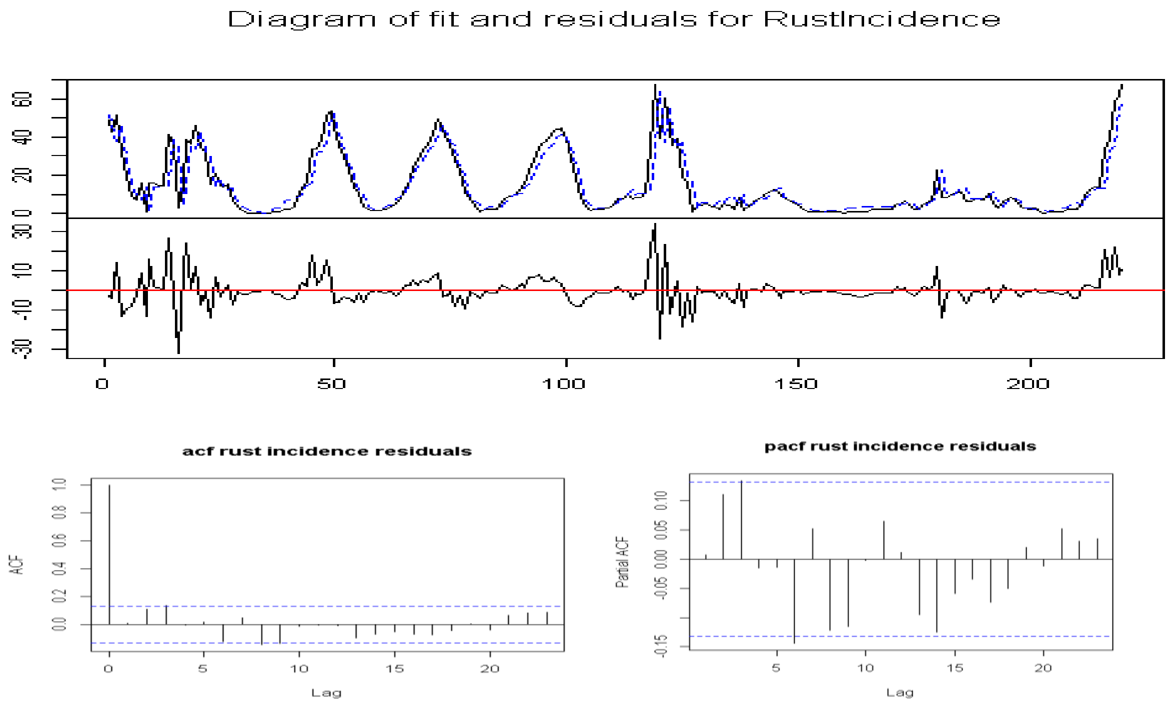


Fig- 3.7 – plot of fit vs residuals and ACF PACF plots of residuals Rust incidence of S795

The above plot shows the plot of fit versus actuals and the residuals. ACF and PACF of residuals has been plotted to show if they are stationary. The ACF and PACF plots of the residuals for rust incidence look fine. This is a sign of stationary residuals.

Severity:

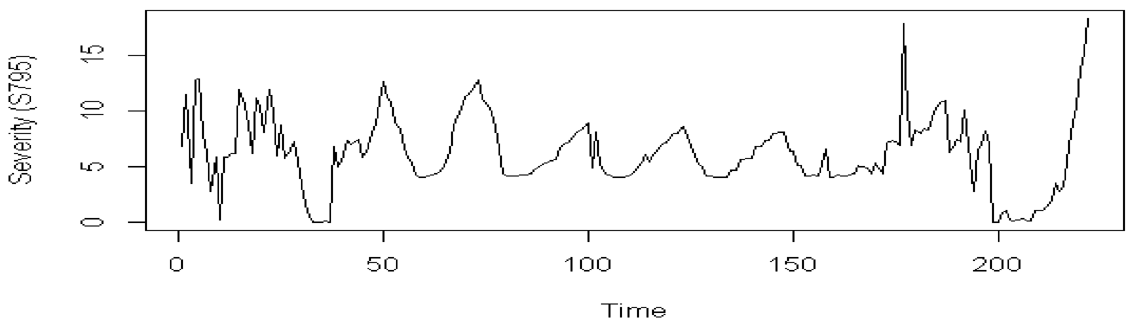


Fig- 3.8 – Time series plot of severity of S795

```
Estimation results for equation Severity:
Severity = TempMax.l1 + RustIncidence.l1 + Severity.l1 + const

                 Estimate Std. Error t value Pr(>|t|)
```

```
TempMax.l1        -0.16457    0.04599  -3.579 0.000436 ***
RustIncidence.l1   0.04419    0.01115   3.965 0.000103 ***
Severity.l1        0.51233    0.06355   8.062  7.4e-14 ***
const              7.09550    1.41527   5.014  1.2e-06 ***
```

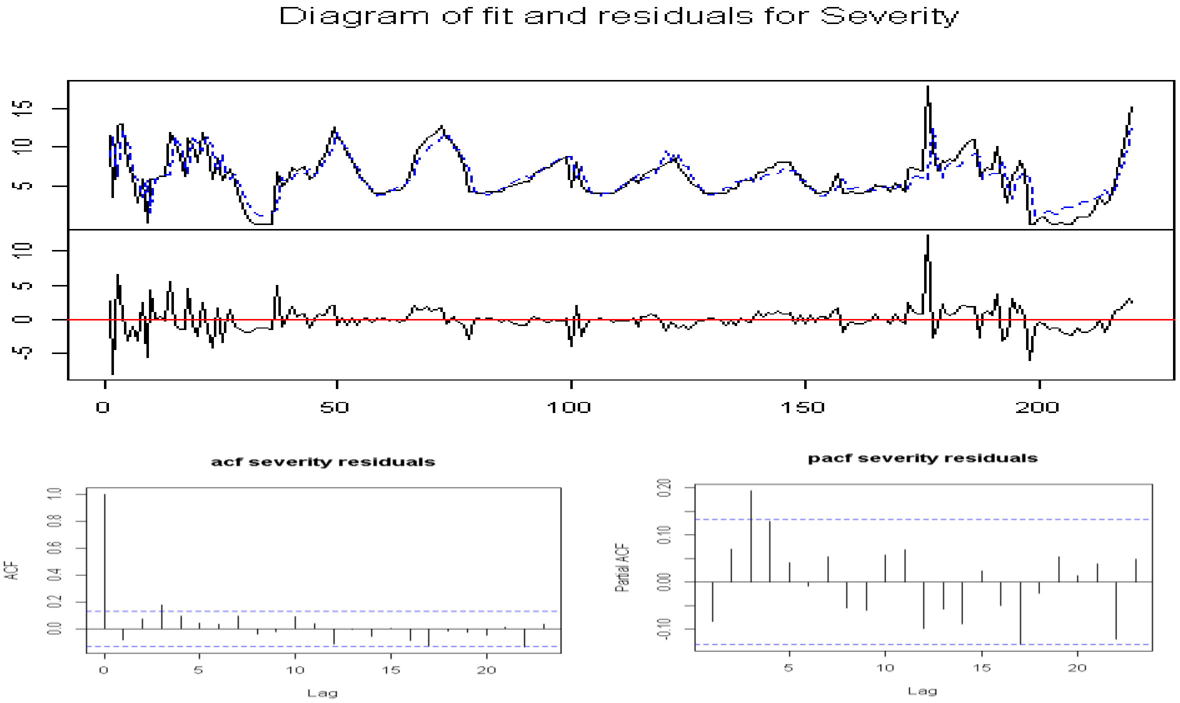


Fig- 3.9 – plot of fit vs residuals and ACF PACF plots of residuals Severity of S795

The above plot shows the plot of fit versus actuals and the residuals. ACF and PACF of residuals has been plotted to show if they are stationary. The ACF and PACF plots of the residuals for severity look fine. This is a sign of stationary residuals.

The multivariate JB test was carried out to check for normality of the residuals. The residuals were found to be non-normal with p value of 2.2e-16.

The portmanteau test was carried out to check for the residuals being white noise. The residuals were indeed found to be white noise with p value of 0.1702

Impulse response analysis:

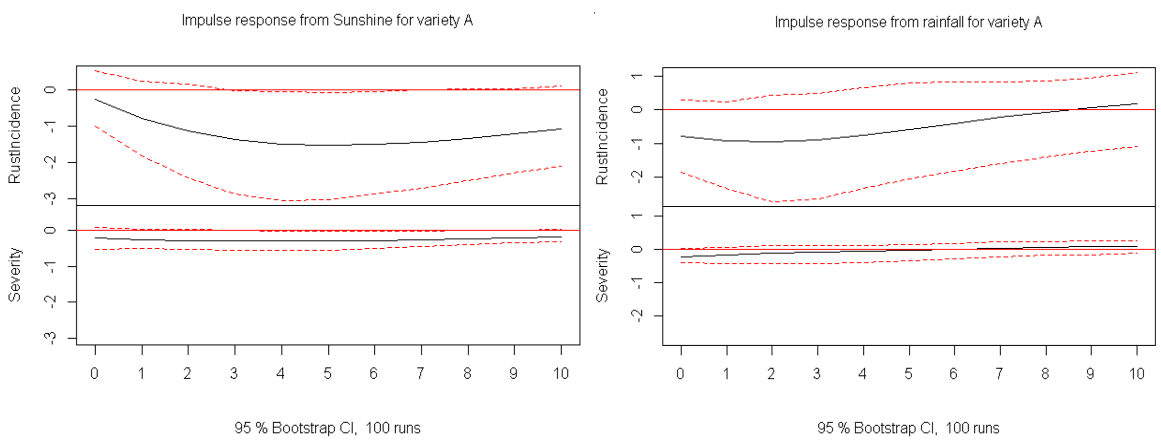


Fig- 3.10 – plots of impulse response from sunshine and rainfall for variety S795 on rust and severity

The IRF plots from the above figure shows that a unit shock in sunshine at let's say time t = 0, has a significant impact on rust incidence and induces rust incidence to decrease in the coming periods. Rainfall also has similar effects on rust incidence.

Severity does not change much in the coming periods after a unit shock in sunshine or rainfall.

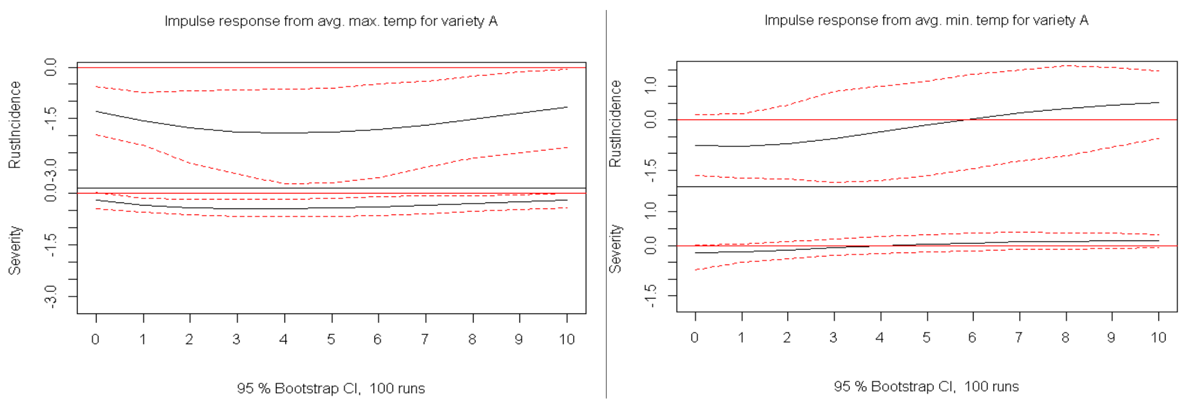


Fig- 3.11 – plots of impulse response from average max and min temperature for variety S795 on rust and severity

A unit shock at let's say t = 0 in average maximum temperature induces rust incidence to decrease in the coming periods. Similarly, for average minimum temperature rust incidence decreases in the coming periods and starts increasing in periods after 5 lags or fortnights.

There is no significant impact on severity from a unit shock in either average maximum temperature or average minimum temperature.

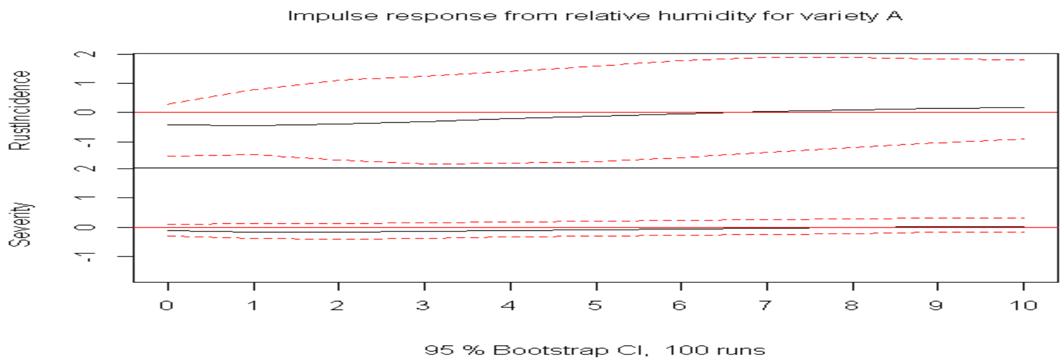


Fig- 3.12 – plots of impulse response from relative hunidity for variety S795 on rust and severity

A unit shock in relative humidity at t =0 does not affect rust incidence or severity in the coming periods. Similarly, severity is not much affected by a unit shock in relative humidity.

Prediction plot

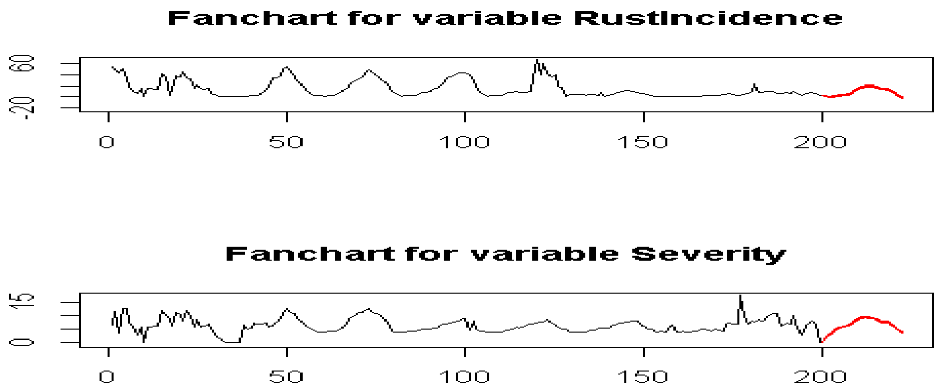


Fig- 3.13 – Fanchart for rust incidence and severity for variety S795

The fanchart for rust incidence and severity show that the two variables will increase and then decrease in the future.

Modelling Sln5B:

Rust incidence:

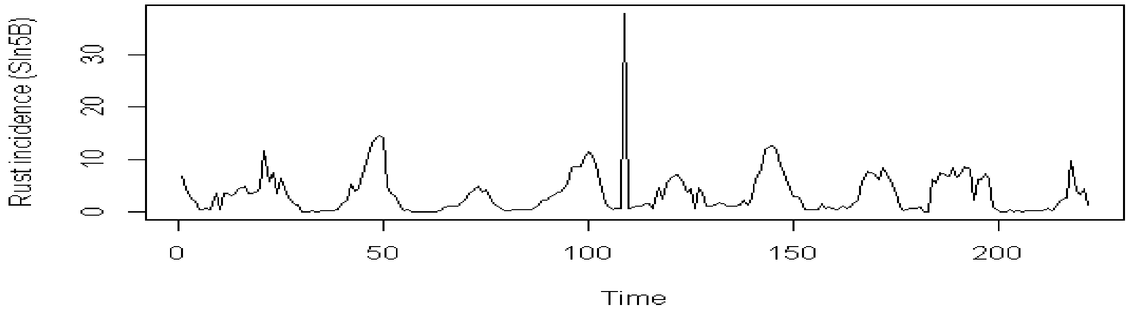


Fig- 3.14 – A time series plot of rust incidence for variety Sln5B

```
Estimation results for equation RustIncidence:
==============================================
RustIncidence = Sunshine.l1 + RainFall.l1 + RelativeHumidity.l1 + Populati
onInfected.l1 + RustIncidence.l1

                       Estimate Std. Error t value Pr(>|t|)
Sunshine.l1           -0.401346   0.175555  -2.286 0.023325 *
RainFall.l1           -0.002579   0.001211  -2.130 0.034410 *
RelativeHumidity.l1    0.039319   0.013692   2.872 0.004538 **
PopulationInfected.l1  0.042969   0.012609   3.408 0.000797 ***
RustIncidence.l1       0.347000   0.071913   4.825 2.82e-06 ***
```

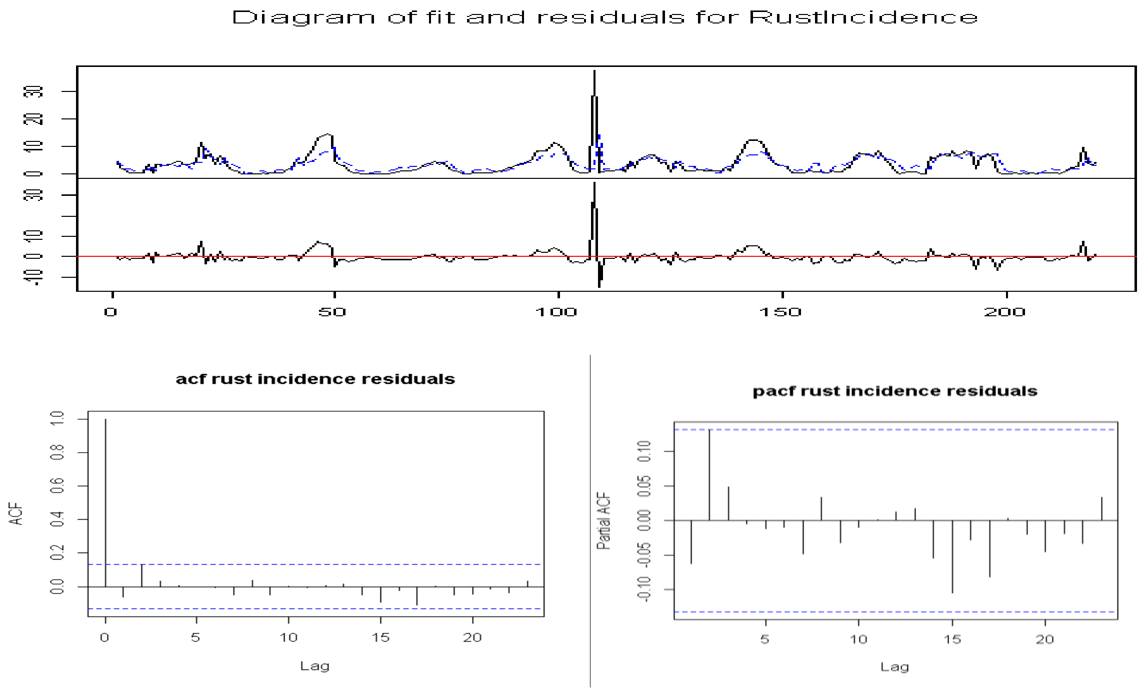


Fig- 3.15 – plot of fit vs residuals and ACF, PACF plots of residuals for rust incidence for variety Sln5

The above plot shows the plot of fit versus actuals and the residuals. ACF and PACF of residuals has been plotted to show if they are stationary.

Severity:

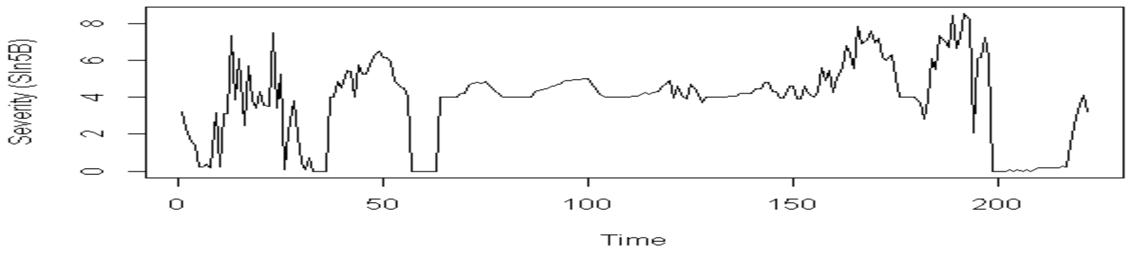
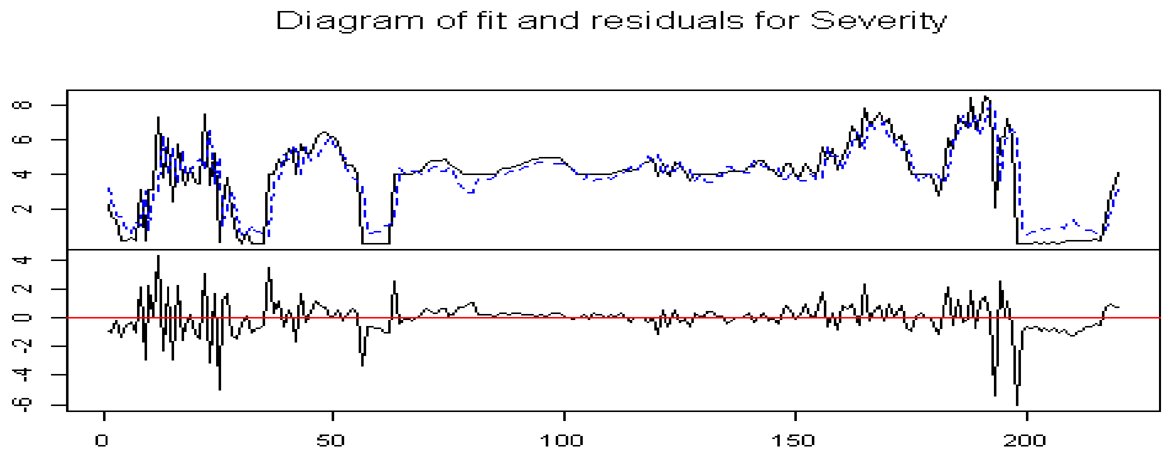


Fig- 3.16 – A time series plot of severity of variety Sln5B

```
Estimation results for equation Severity:
=========================================
Severity = Sunshine.l1 + TempMin.l1 + PopulationInfected.l1 + Severity.l1

                       Estimate Std. Error t value Pr(>|t|)    
Sunshine.l1           -0.184664   0.051639  -3.576 0.000440 ***
TempMin.l1             0.106565   0.018094   5.890 1.67e-08 ***
PopulationInfected.l1  0.017341   0.005017   3.456 0.000672 ***
Severity.l1            0.592919   0.062730   9.452  < 2e-16 ***
```



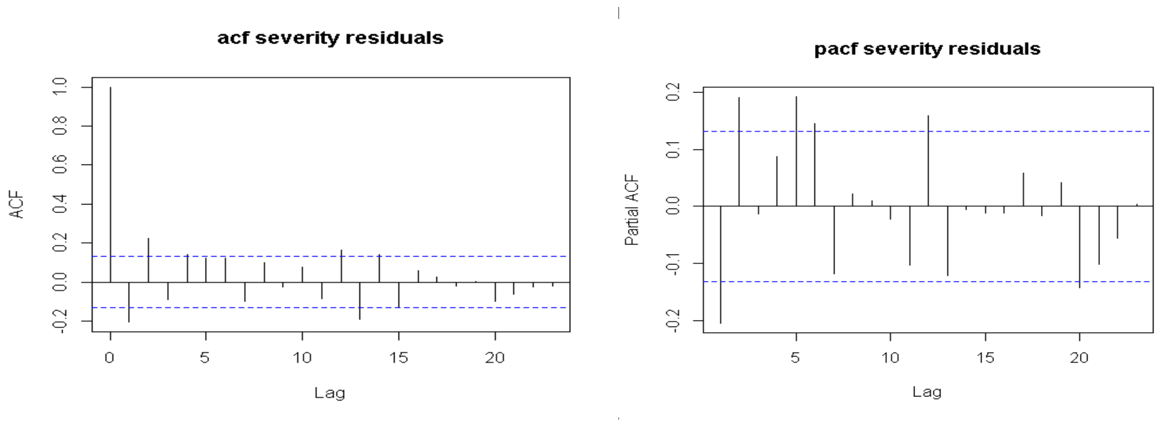


Fig- 3.17 – plot of fit vs residuals and ACF, PACF plots of residuals for severity for variety Sln5

The above plot shows the plot of fit versus actuals and the residuals. ACF and PACF of residuals has been plotted to show if they are stationary. The ACF and PACF plots of the residuals for severity look fine. This is a sign of stationary residuals.

The multivariate JB test was carried out to check for normality of the residuals. The residuals were found to be non-normal with p value of 5.74e-14.

The portmanteau test was carried out to check for the residuals being white noise. The residuals were indeed found to be white noise with p value of 0.0823

Impulse response analysis

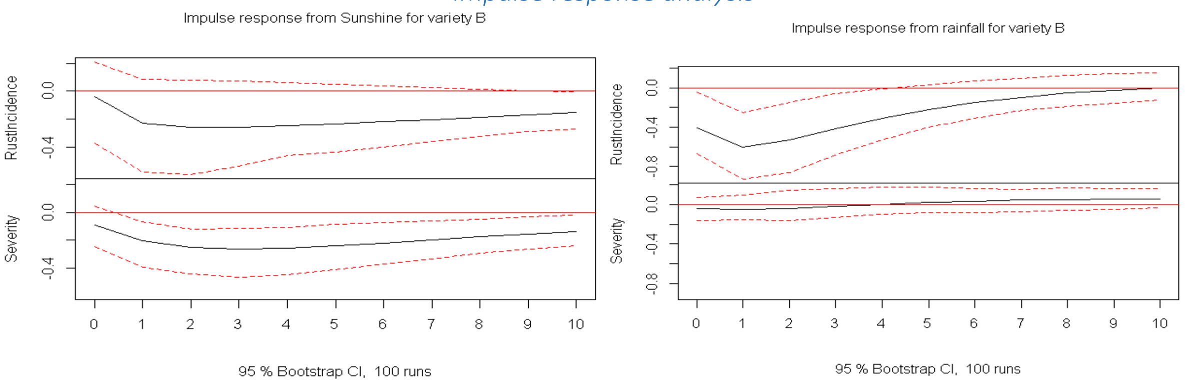


Fig- 3.18 – plots of impulse response from sunshine and rainfall for variety Sln5B on rust and severity

The IRF plots from the above figure shows that a unit shock in sunshine at let's say time t = 0, has a significant impact on rust incidence and induces it to decrease in the coming periods. Rainfall also has similar effects on rust incidence.

Severity is induced to decrease in the coming periods after a unit shock in sunshine. Severity does not change much in the coming periods after a unit shock in rainfall.

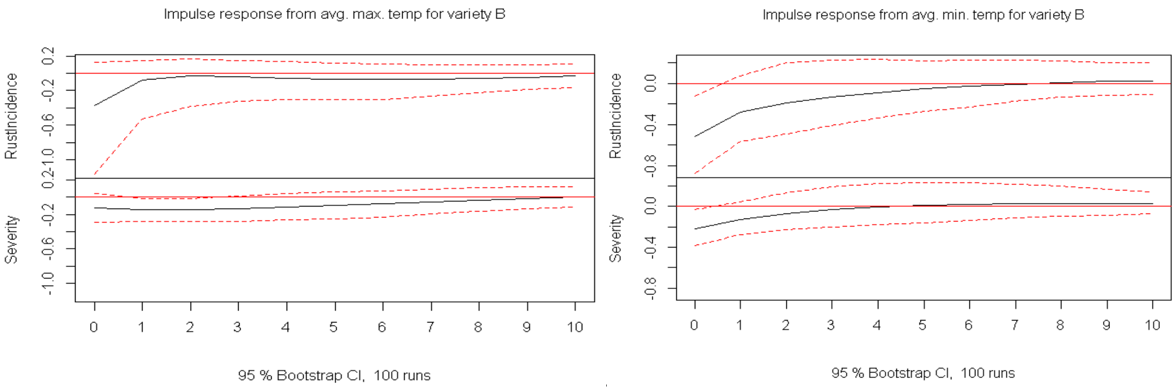


Fig- 3.19 – plots of impulse response from avg max and min temperature for variety Sln5B on rust and severity

A unit shock at let’s say t = 0 in average maximum temperature induces rust incidence to decrease in the coming periods. Similarly, for average minimum temperature rust incidence decreases in the coming periods.

Unit shock in average maximum temperature induces severity to decrease in the coming periods.

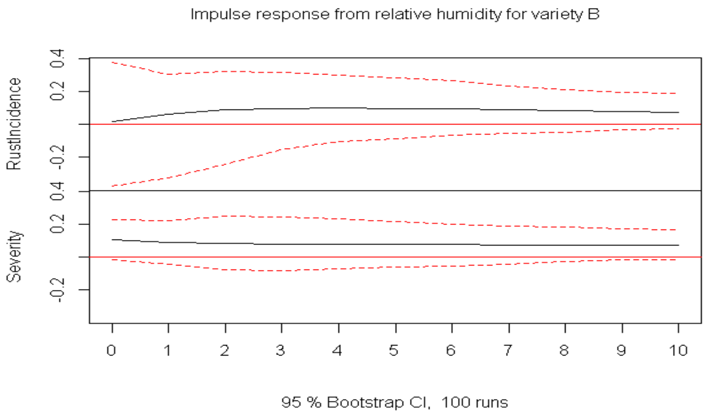


Fig- 3.20 – plots of impulse response from relative humidity for variety Sln5B on rust and severity

A unit shock in relative humidity at t =0 induces the rust incidence to increase in the coming periods. Severity is also affected in a similar fashion by a unit shock in relative humidity.

Prediction plot

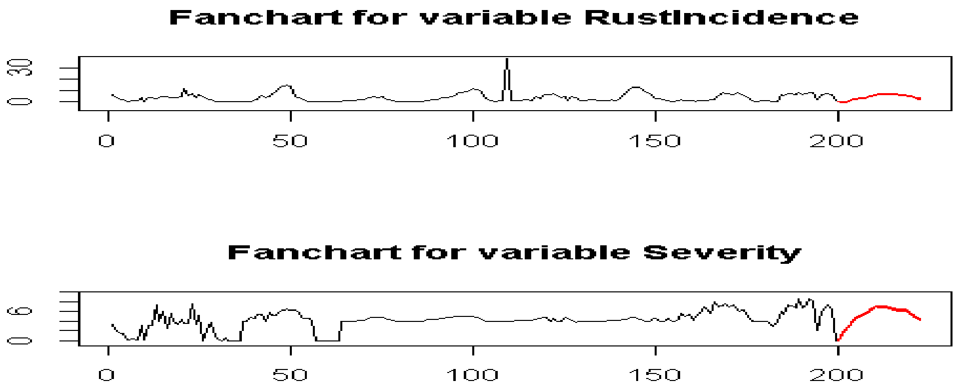


Fig- 3.21 – Fanchart for rust incidence and severity for variety Sln5B

The fanchart for rust incidence and severity show that the two variables will increase and then decrease in the future.

Modelling CXR:

Rust incidence:

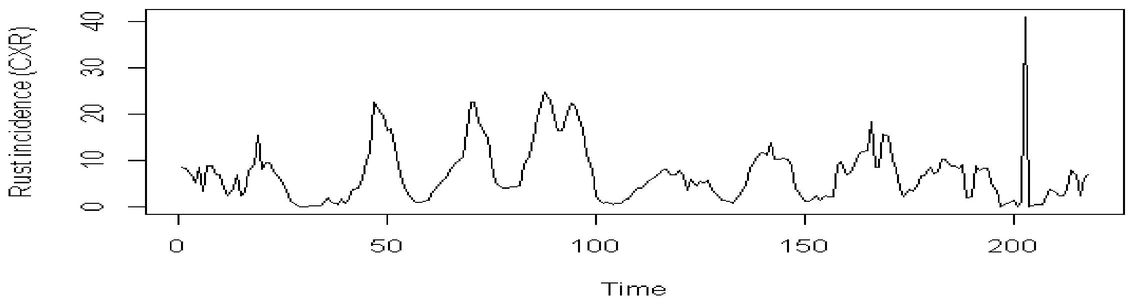


Fig- 3.22 – Time series plot of rust incidence for variety CXR

```
Estimation results for equation RustIncidence:
==============================================
```

```
RustIncidence = RainFall.l1 + TempMax.l1 + TempMin.l1 + RelativeHumidity.l
1 + PopulationInfected.l1 + RustIncidence.l1

                        Estimate Std. Error t value Pr(>|t|)
RainFall.l1            -0.003243   0.001440  -2.253 0.025317 *
TempMax.l1             -0.189367   0.086906  -2.179 0.030439 *
TempMin.l1             -0.497049   0.217853  -2.282 0.023512 *
RelativeHumidity.l1     0.185665   0.050201   3.698 0.000277 ***
PopulationInfected.l1   0.059147   0.019653   3.010 0.002935 **
RustIncidence.l1        0.518575   0.071922   7.210 9.82e-12 ***
```

Out of the weather variables, average maximum temperature, average minimum temperature and relative humidity are significant at lag 1.

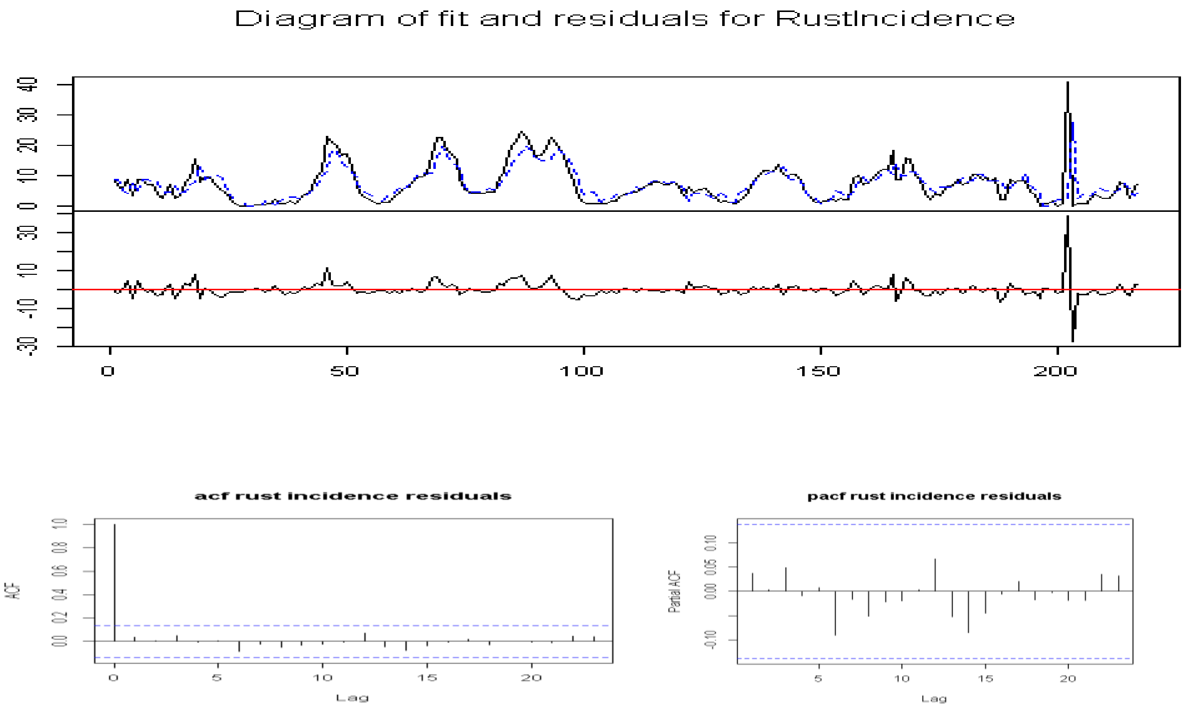


Fig- 3.23 – plot of fit vs residuals and ACF, PACF plots of residuals for rust incidence for variety CXR

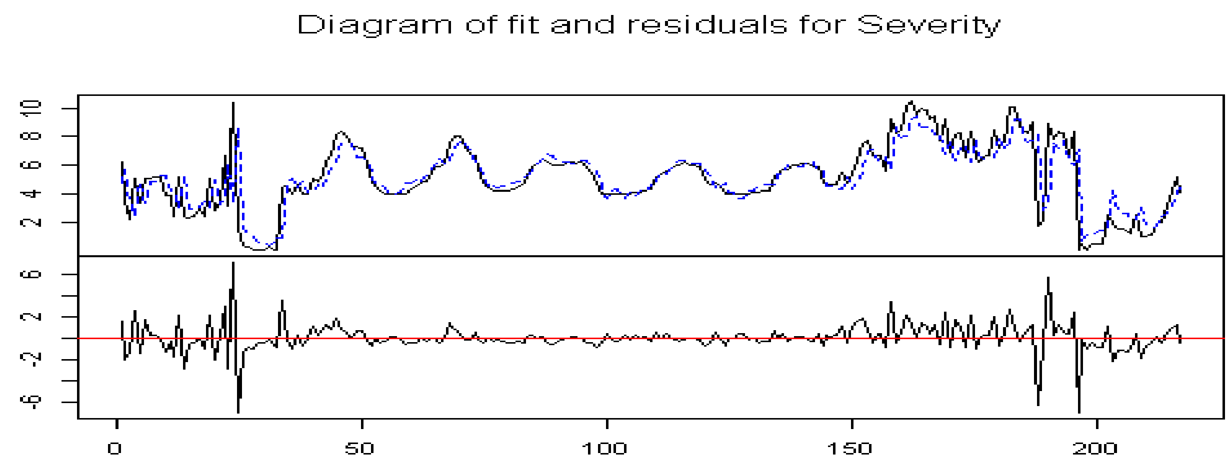
The above plot shows the plot of fit versus actuals and the residuals. ACF and PACF of residuals has been plotted to show if they are stationary. The ACF and PACF plots of the residuals for severity look fine. This is a sign of stationary residuals.

Severity:

```
Estimation results for equation Severity:
=========================================
Severity = Sunshine.l1 + RelativeHumidity.l1 + PopulationInfected.l1 + Sev
erity.l1

                      Estimate Std. Error t value Pr(>|t|)
Sunshine.l1          -0.116938   0.054151  -2.159 0.031931 *
RelativeHumidity.l1   0.013809   0.003765   3.668 0.000309 ***
PopulationInfected.l1 0.018188   0.006559   2.773 0.006047 **
Severity.l1           0.704173   0.055770  12.626  < 2e-16 ***
```

Sunshine, relative humidity, population infected and severity at lag 1 are significant.



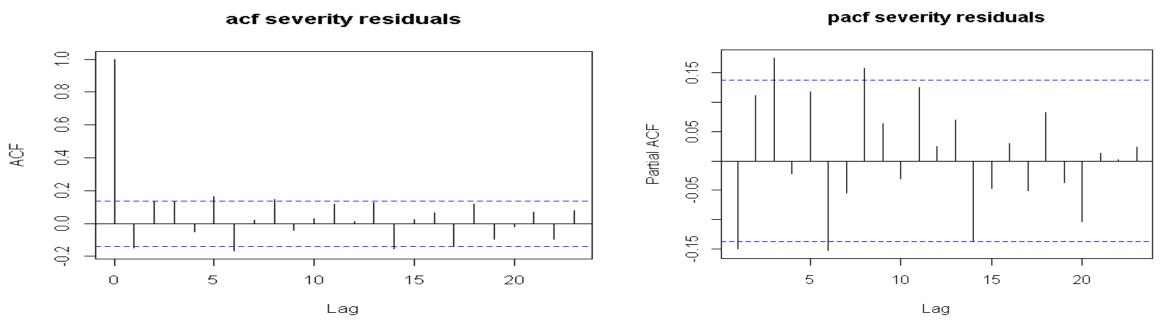


Fig- 3.24 – plot of fit vs residuals and ACF, PACF plots of residuals for severity for variety CXR

The above plot shows the plot of fit versus actuals and the residuals. ACF and PACF of residuals has been plotted to show if they are stationary. The ACF and PACF plots of the residuals for severity look fine. This is a sign of stationary residuals.

The multivariate JB test was carried out to check for normality of the residuals. The residuals were found to be non-normal with p value of 2.2e-16.

The portmanteau test was carried out to check for the residuals being white noise. The residuals were indeed found to be white noise with p value of 0.2104

Impulse response analysis:

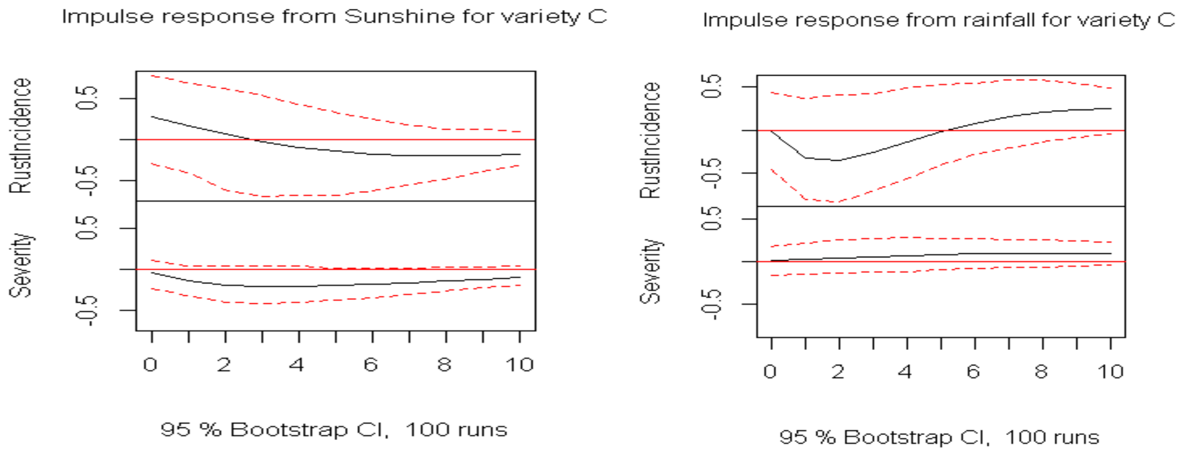


Fig- 3.25 – Impulse response plots from Sunshine and rainfall for variety CXR

A unit shock in sunshine at time t =0, induces the rust incidence to increase in the coming period and then it starts decreasing after second period. Severity is induced to decrease due to a unit shock in sunshine.

A unit shock in rainfall at time t =0, induces the rust incidence to decrease in the coming period and then it increases after 5th period. Severity does change much due to a unit shock in rainfall.

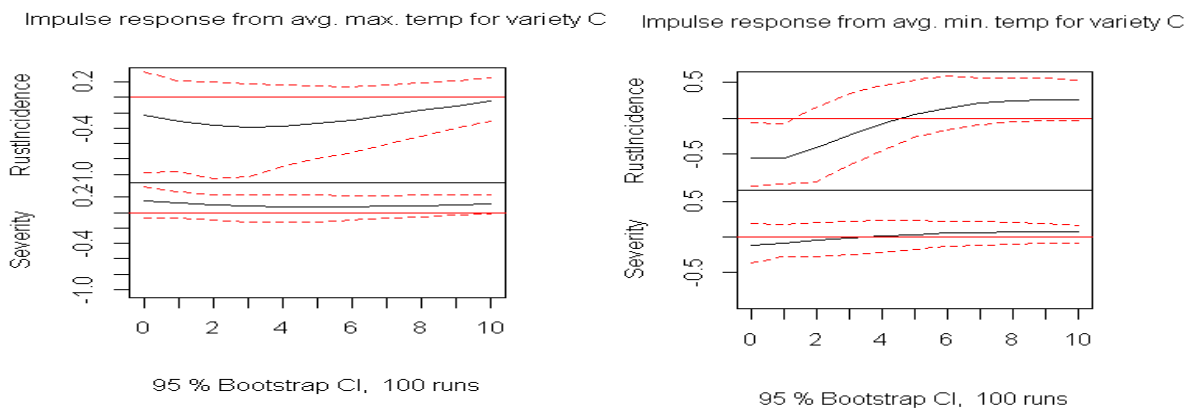


Fig- 3.26 – Impulse response plots from average max and min temperature for variety CXR

A unit shock in average maximum temperature at time t = 0, induces rust incidence to decrease in the coming period and induces severity to increase in the coming periods.

A unit shock in average minimum temperature at time t = 0, induces rust incidence to decrease in the coming periods and then increase after 4th period. Severity is not much affected due to a unit shock in average minimum temperature.

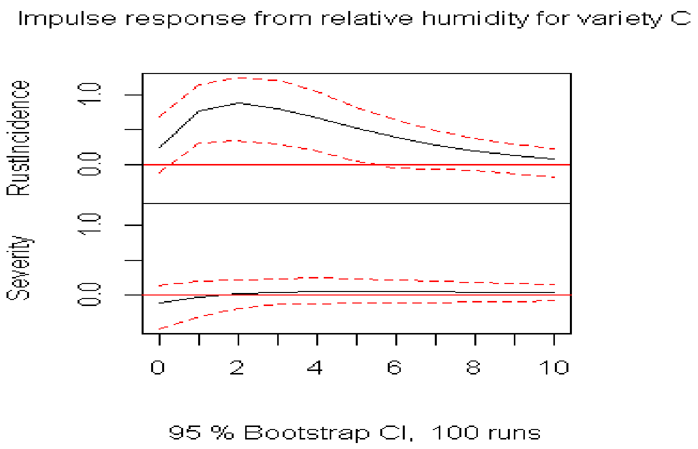


Fig- 3.27 – Impulse response plots from relative humidity for variety CXR

A unit shock in relative humidity at time t = 0, induces rust incidence to increase in the coming period but the same shock does not affect severity much.

Prediction plot

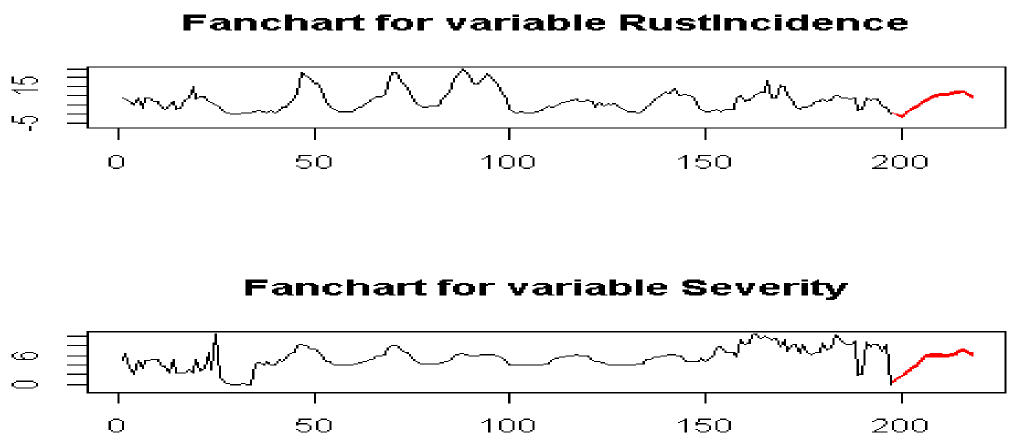


Fig- 3.28 – Fanchart for variety CXR

The fanchart shows that both rust incidence and severity will increase in the future.

Forecasting

To forecast the disease variables based on the forecasted weather variables, the dataset containing all 8 variables was split into two categories and then fed into VAR. Weather variables were used as exogenous regressors in the VAR model, while disease variables were used as endogenous variables in the model. I had to forecast the disease variables based on the forecasted weather variables.

Out-of-sample forecast

To check the accuracy of the VAR model out of sample forecasting with a rolling origin was done and accuracy of the same was noted. The forecasts and forecasting accuracy has been shown in the latter part of the report when comparison with LSTM has been done.

Chapter Four

Recurrent neural network

Recurrent neural networks are artificial neural networks with cycles [9]. These architectures are the natural architecture for sequence learning tasks. Recurrent neural networks (RNNs) are connectionist models with the ability to selectively pass information across sequence steps, while processing sequential data one element at a time. RNNs retain information over long sequences and are perfectly capable of retaining information from very long sequences. This property has led them to be considered as universal sequence approximators and can learn any sequence [9]. But this has not been observed in practice and recurrent neural networks suffer from vanishing and exploding gradients problem. To address this issue the nodes in the hidden layers of the network are replaced by so called memory blocks. The architectural variant of recurrent neural networks with memory blocks are referred to as long short-term memory (LSTM) [8]. One of the papers [8] I went through had done a review of recurrent neural network and I am using few of those images to illustrate the functioning of a recurrent neural network.

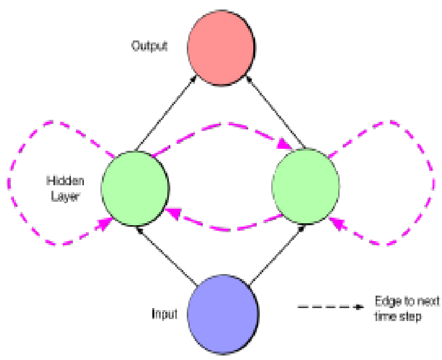


Fig:4.1 A simple RNN[8]

Input to the network through the input layer is just called input. Units in the hidden layer calculate a weighted sum of the input from the input layer. This weighted sum is known as network input to the input, h, and denote it a_h [9].

The above figure shows an input layer, a hidden layer and an output layer of a recurrent neural network. Input at time 't', to the network goes through the input layer to the nodes in the hidden layer. The nodes in the hidden layer apply an activation function on the network input i.e. weighted input from the input layer. Then the activations move to the output layer, exactly as in a feed forward neural network. The activations from time step 't' go back to the node as network input at time step ‘t+1’. That is the activations arrive at the hidden layer from both the current external input and hidden layer activations from the previous time steps.

Network Training:

Loss function:

It is a function of the difference between predicted and true values of the variable to be predicted. This function should be differentiable and that will enable training of the network through gradient descent. Choice of loss function must be based on the task at hand. The task here is of regression so I have used mean squared error as the loss function which is differentiable.

Back propagation through time:

Back Propagation is a repeated application of chain rule of partial derivatives. The loss function, which must be minimized, is differentiated with respect to the output units.

Training of an RNN is done by Back Propagation Through Time (BPTT). BPTT is like Back propagation and consist of repeated application of chain rule. It is important to note that the loss function depends on the hidden layer through [9]:

a) The influence of the hidden layer on output layer.
b) Influence of the hidden layer on the next time step.

Unfolding:

For ease of understanding RNNs can be visualized by unfolding the network along the input sequence. An unfolded RNN is shown below.

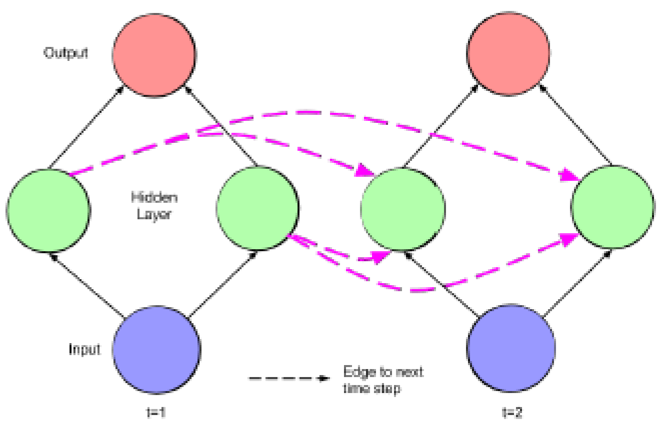


Fig- 4.2 Unfolded RNN [8]

The network can be interpreted as not cyclic but like a feed forward network that has one layer for each time step. The network also consists shared weights across time steps. This picture makes it clear how back propagation can be applied across many timesteps so that the network can be trained [8].

Vanishing and exploding gradients

Due to the requirement of learning long range dependencies, learning with recurrent neural networks can be especially challenging [8]. When back propagating gradients across many timesteps the problems of vanishing and exploding gradients occur. The influence of a given input on the hidden layer and therefore on the network output, either decays or blows up exponentially as it cycles around the recurrent connections of the network.

Vanishing gradients problem refers to the exponential decay of gradients in terms of magnitude as they are propagated back through time. This causes the memory to ignore long-term dependencies and not learn any association between two events separated by long lag [10].

Next major problem is of exploding gradients. When the network has to learn over long range dependencies the gradients explode when the weights are big. This problem refers to the fact that the large increase in the norm of the gradient during training sequences with long-term dependencies leads to the explosion of long-term components [10].

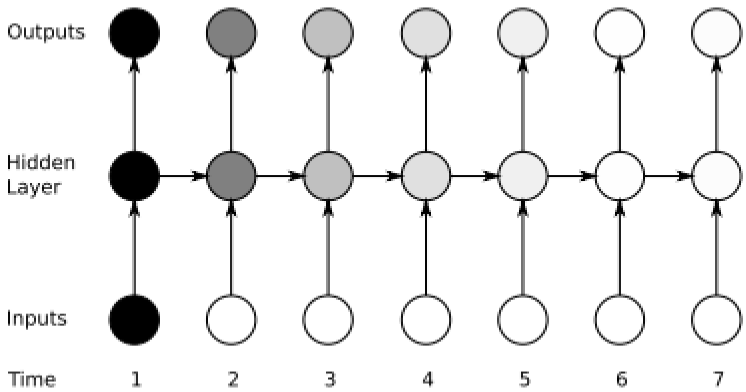


Fig 4.3: Vanishing gradient problem for RNN

The shading of the nodes in the unfolded network indicate the sensitivity to the inputs at time 1. The sensitivity decreases over time as new inputs overwrite the activations of the hidden layer and the network forgets its first inputs.

LSTM:

The long short-term memory (LSTM) architecture was proposed in 1997, primarily to deal with the problem of exploding and vanishing gradients by Hochreiter and Schmidhuber [8], [10]. The LSTM architecture replaces nodes in the hidden layer of an RNN by an LSTM memory block. The block contains a node with self-connected recurrent edge of fixed weight 1. This ensures that the gradients can pass across many timesteps without vanishing or exploding [8].

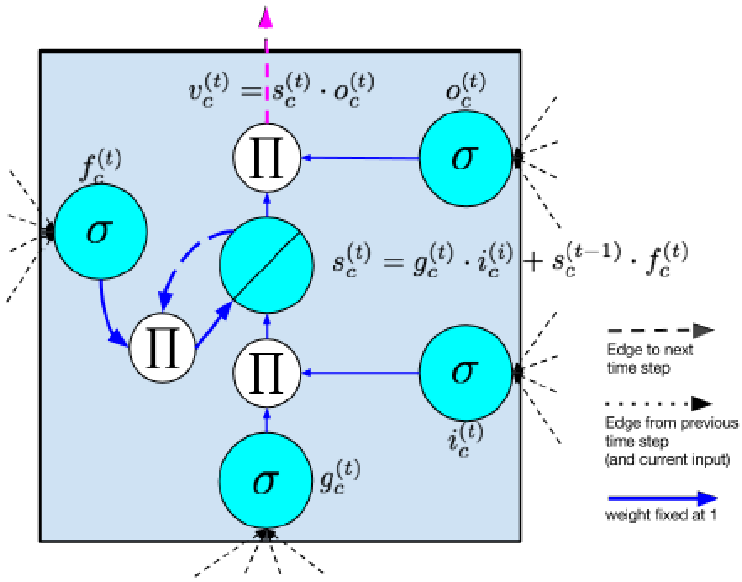


Fig 4.4 . An LSTM memory block. Source: [8]

The supervised learning tasks on which LSTM has been successfully applied to are Natural language translation, image captioning, time series forecasting etc. [8]

Hyper parameters tuning

Hyper parameter tuning is one of the most important aspect of machine learning. To find the optimal combination of the hyper parameter is an iterative process of searching among the infinite possibilities of hyperparameters. One of the most important hyperparameters that needs to be tuned is the learning rate. There have been previous research efforts over explaining if any dependencies among the hyperparameters [11]. The most critical components of the LSTM architecture found was the forget gate and the output activation function. The hyperparameters appeared virtually independent [11]. It was found that for practical purposes hyperparameters can be treated as approximately independent and can be optimized separately [11]. For this project the hyperparameters were tuned separately using grid search, implemented in python.

Notes on tuning:

- There is no apparent hyperparameter interactions structure [11].
- For all practical purposes the hyperparameters can be treated approximately independent [11].

Approach towards tuning:

- Optimizer was tuned first through grid search.

- Then network size, activation function, weight initializer was tuned. (not in order)
- Regularizers were tuned then.
- Number of epochs and batch size was tuned first using grid search.
- Final selection of optimal hyperparameters was done after final tuning by hand.

Tuned Hyperparameters:

A total of six LSTM models were tuned for the six variables that had to be predicted. All of them were optimized using nadam optimizer. Initializer, activation function, optimizer, batch size and number of layers was common across all the six models. L2 regularization was used in all the six models.

Dropout has been very successful in the feed forward neural networks, but it does not have much empirical evidence suggesting successfull application of the same in recurrent neural networks [12]. They show that using dropout can greatly reduce overfitting in LSTM models. I have used dropout and recurrent dropout both in few of the models. Dropout indeed reduces overfitting for this problem.

Below is a table showing the final hyperparameters:

Hyper parameters	S795 rust	S795 severity	Sln5B rust	Sln5B severity	CXR rust	CXR severity
Layers	1	1	1	1	1	1
Neurons	3	3	5	10	5	8
Initializer	Glorot normal	Glorot Normal	Glorot Normal	Glorot Normal	Glorot Normal	Glorot Normal
activation	elu	elu	elu	elu	elu	elu
Optimizer	Nadam	Nadam	Nadam	Nadam	Nadam	Nadam
Regularizer	L2	L2	L2	L2	L2	L2
Dropout	0.005	None	None	0.03		0.005
Recurrent dropout	None	0.40	0.01		0.5	0.5
Batch size	1	1	1	1	1	1
Epochs	100	60	100	100	100	100

Loss Curves:

This section illustrates the loss curves for the given hyperparameters in the above table. Blue line shows the loss in training and orange ones show the loss during validation.

For the variety CXR the loss curves show good generalisation as compared to the other two varieties.

Some of the models are generalizing well and in some cases the validation loss is low compared to the training loss. This could be because the data for validation was ‘easy’ to predict as compared to the data used for learning during training. Different train/test splits could not be tried in this case as this is a time series problem, so splitting randomly is out of question. And the number of data points are less, i.e. around 20.

Variety S795:

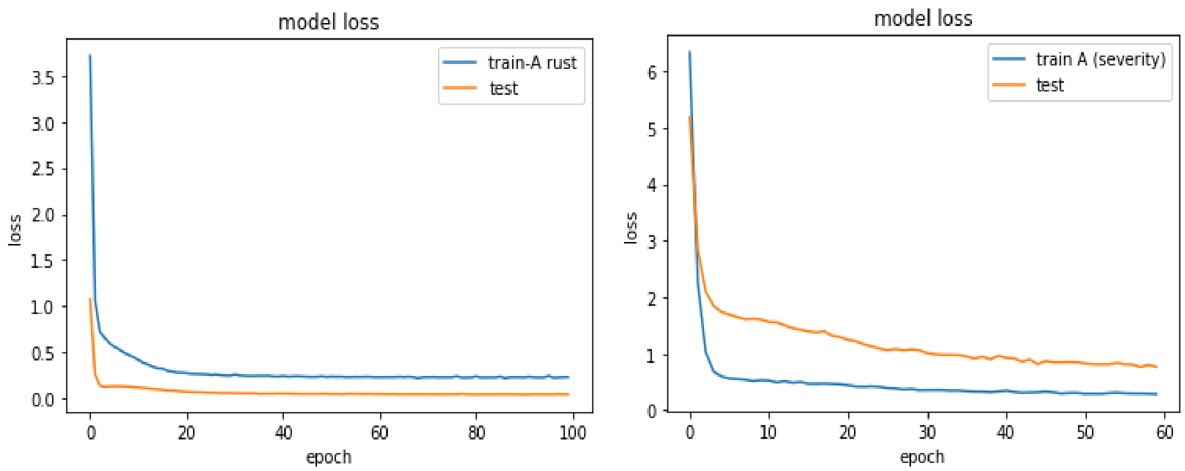


Fig- 4.5 Model loss for variety S795

Variety Sln5B:

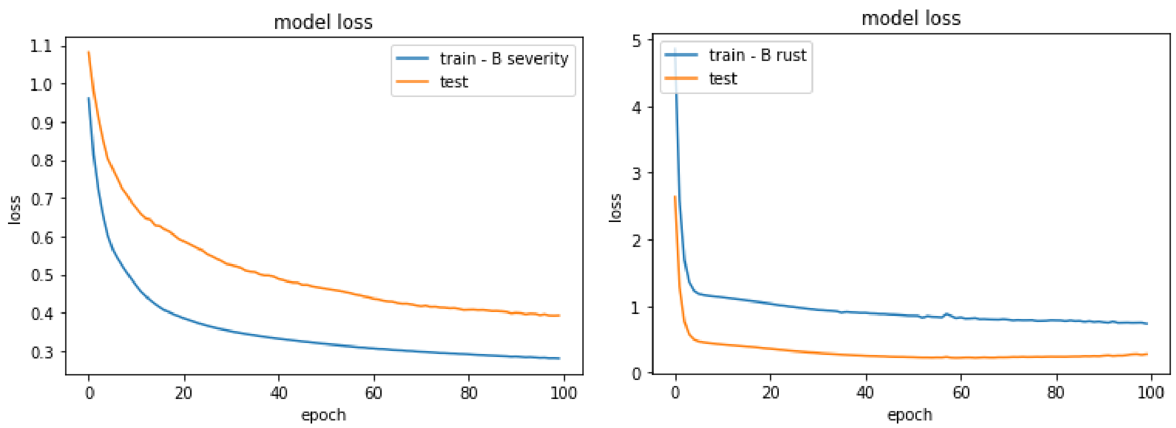


Fig- 4.6 Model loss for variety Sln5B

Variety CXR:

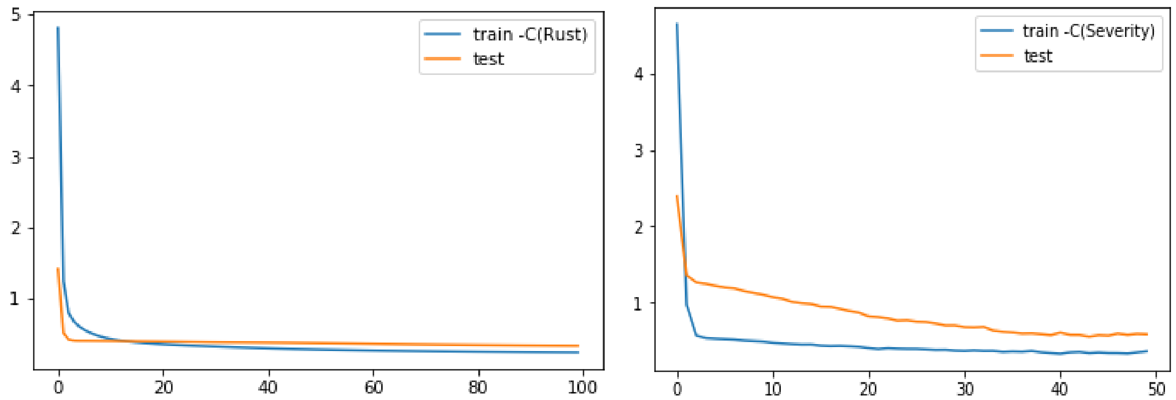


Fig- 4.7 Model loss for variety CXR

Chapter Five

Comparison of forecasts from VAR and LSTM:

Forecasting with rolling origin was done and two error metrics were noted. They are:

a) Root mean squared error (RMSE)
b) Mean relative squared error (MRSE)

RMSE and MRSE both should be small for good forecasts. MRSE measures the goodness of a forecast as compared to predicting the mean of the variable every time. RMSE is an absolute measure of error and is affected by scale of the vaiables.

Variety S795:

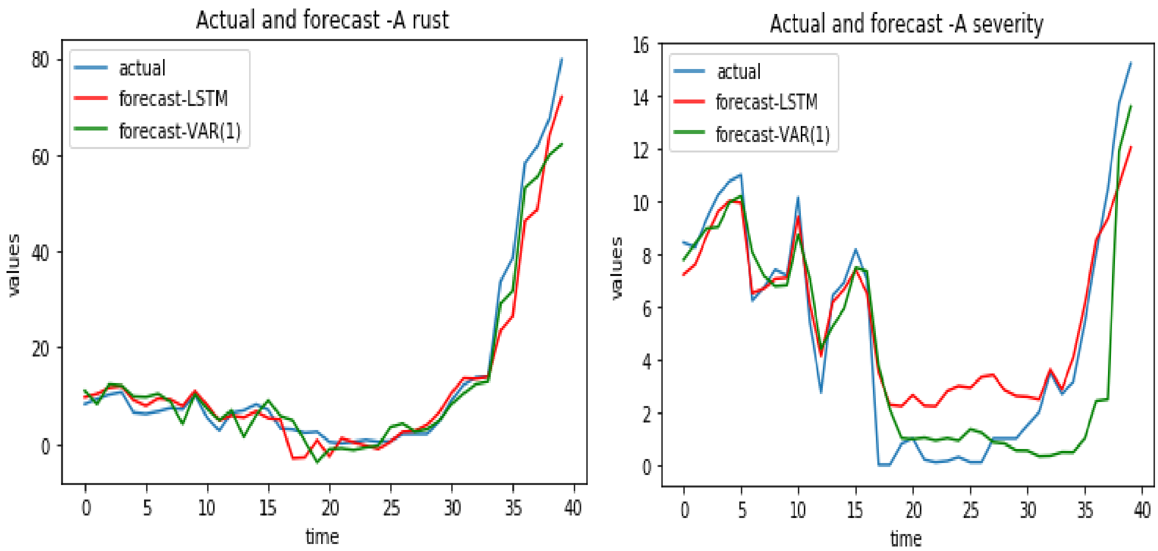


Fig- 5.1 prediction plots for variety S795 VAR and LSTM

	RMSE	MRSE
LSTM	4.41	0.22
VAR	4.16	0.21

	RMSE	MRSE
LSTM	1.64	0.38
VAR	2.17	0.52

Variety Sln5B:

Rolling forecasts

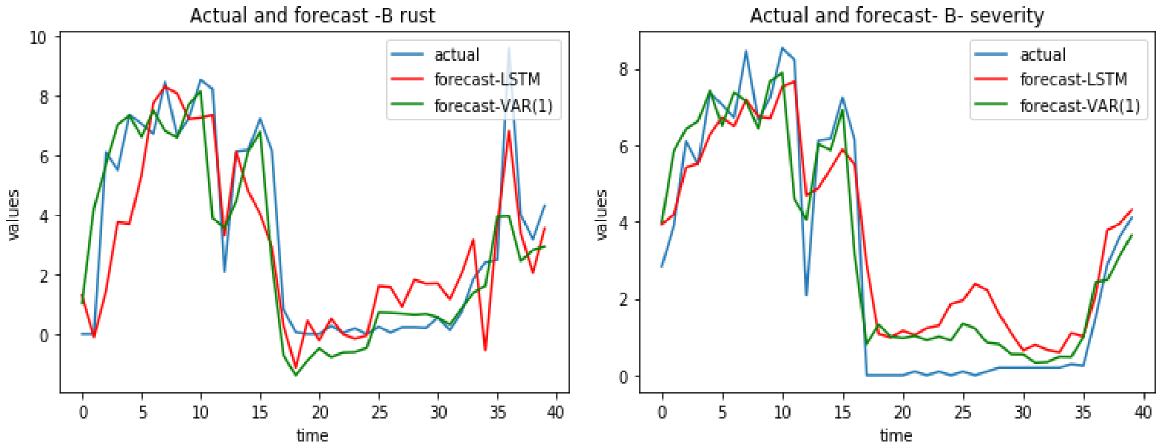


Fig- 5.2 prediction plots for variety Sln5B VAR and LSTM

	RMSE	MRSE
LSTM	1.65	0.511
VAR	1.67	0.516

	RMSE	MRSE
LSTM	1.18	0.37
VAR	1.11	0.35

Variety CXR:

Rolling forecasts:

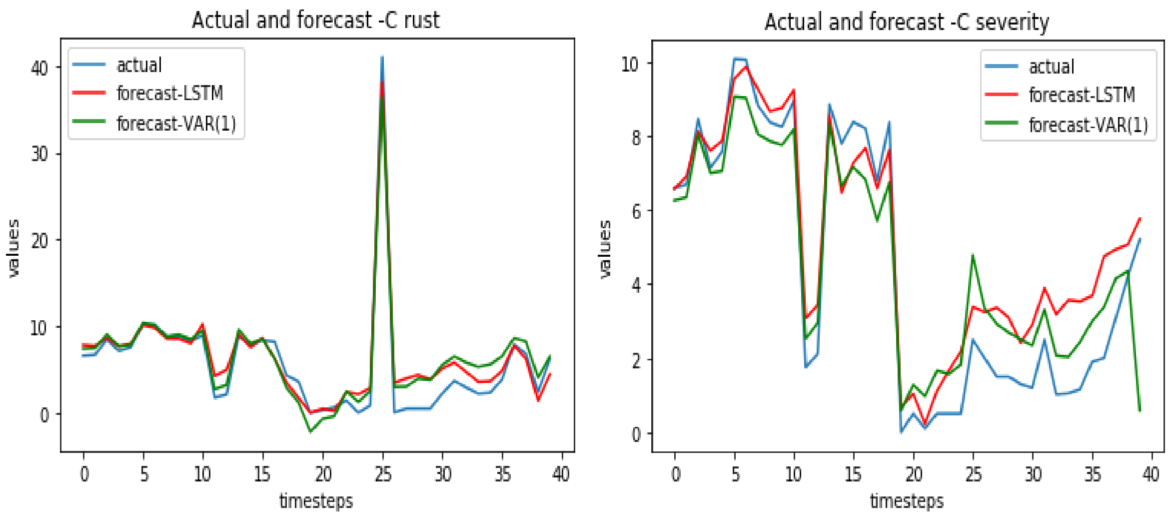


Fig- 5.3 prediction plots for variety CXR VAR and LSTM

	RMSE	MRSE
LSTM	1.73	0.26
VAR	1.93	0.29

	RMSE	MRSE
LSTM	1.22	0.36
VAR	1.26	0.37

Conclusion:

The major objective of this work was prediction of coffee leaf rust incidence and severity. The same was accomplished using VAR and LSTM.

Inferences using impulse response analysis was drawn which showed how a unit shock in weather variables induce disease variables to change in the coming period.

VAR, along with forecasts provides tools for interpretation of the relationships among the weather and disease variables. LSTM is a complex machine learning model. It lacks tools for interpretation but at the same time it has outperformed VAR in four out of six predictions, i.e. rust incidence and severity for each of the three varieties.

Three VAR(1) model were developed for forecasting for all the three varieties and a total of six LSTM models were developed for predicting the same.

Based on the data and the approach taken in this work, LSTM is recommended for forecasting the rust incidence and severity while VAR must be used for understanding the structural relationships among the weather and disease variables.

Future work:

With more data machine learning model's performance increases and so with new data one can expect to get better forecasting accuracy for LSTM than that is achieved now.

Hybrid models can be used for improving the forecasts. VAR can be used to model the multivariate time series and the residuals from VAR can be modelled using RNN.

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