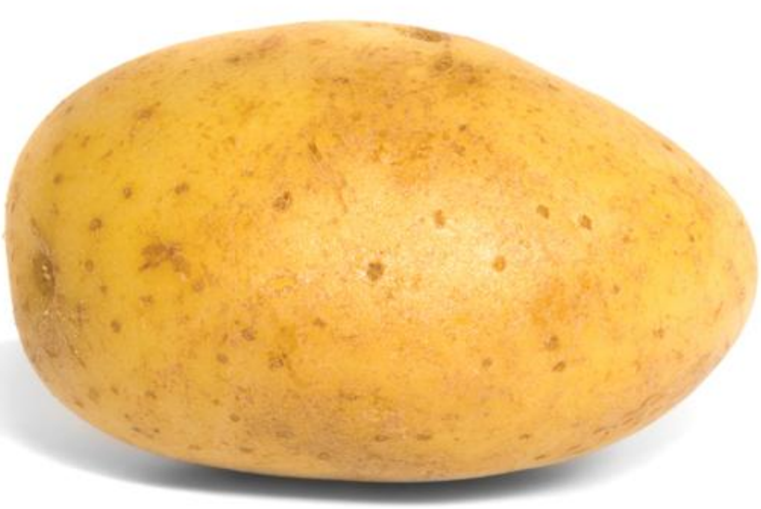
CHAPTER–II

Review of Literature



REVIEW OF LITERATURE

2.1 Introduction

Potato is a major food crop after wheat, rice and maize in the world. In the Indo-Gangetic region of India extensive recent and older alluvium is ideal for potato cultivation during rabi season. The area and production of potato has increased from 18.63 lakh ha to 19.92 lakh ha and 42.34 million tons for 45.34 million tons during 2010-11 and 2012-13. Irrespective of the good production, modern agricultural practices in the last few decades invited a large number of insect and pests in potato crop which affected the crop production as well as quality of potato (Thakur et al., 2012). More than 175 disorders of potato due to disease and pest have been reported by Wellman (1972) whereas Shekhawat (1990) short listed about 24 disease or disorders of potato crops in India. However, the potato crop is very sensitive to biotic and abiotic stresses and suffers from many pests and diseases among which late blight, caused by the Oomycete *Phytophthora infestans,* is the worst. The disease is still causing major damage in many potato producing areas and control is only possible by applying fungicides on a routine basis irrespective of the disease occurrence to keep the bacteria at bay. Full potential of the crop can be realized only if diseases and pests are kept under control.

2.2 History and Distribution of Potato Late Blight

Since 1944 – 1945, the late blight became one of the most concerned disease of potato throughout the world. It reduces global potato production by around 15%. Although the severity levels of late blight in sub-tropical region is moderate as compare to Latin America and European countries but it is most severe in India where, average late blight severity is over 70% followed by Nepal 64%, Pakistan and China 58%. The potato late blight severity levels is not uniform throughout the whole country. The late blight disease is most severe in temperate high land followed by sub-tropical plains (Singh and Shekhawat, 1999). Even in sub-tropical plains the disease is generally more regular and severe in north-eastern plains of Assam, Bihar, West Bengal and Orissa as compared to western plains. This Variation in disease severity are primarily due to many biotic factors and difference in weather conditions (Sing and shekhawat 1999).

Among biotic factors many disease causing agents viz. fungus like oomycete, viruses, bacteria, nematode, viroids and phytoplasmas are reported on potato. Among these disease caused by filamentous oomycete, *Phytophora infestans*, is most devastating. Very few crop losses have been as devastating as those caused by potato late blight in the 1840's. The origin of *Phytophora infestans* is thought to be in the Toluca valley of Maxico where many different strains evolve alongside wild potato relatives (Yoshida et al., 2013). In 1845, the pathogen finally reached Europe, spreading rapidly from Belgium to other countries of mainland Europe and then to Great Britain and Ireland. The impact of the epidemic reached catastrophic levels in Ireland, where the population was more dependent on potato for their subsistence than in other parts of Europe (Bourke, 1964, Reader, 2009). The subsequent Great Faminine killed around one million people, and an additional million were forced to leave the island (Turner, 2005). Even today, the Irish population remains less than three quarters of what it was at the beginning of the 1840's (Yoshida et al., 2013).

Phytophora infestans came to India with imported seed potatoes from Europe. In India, the late blight appears in epiphytic form every year in Himalayan and Nilgiri hills, in some areas in Indo-Gangetic plains and sporadically in cold deserts and central and Decan Platue (Dutt, 1979). It was recorded in India for the first time between 1870-1880 in the Nilgiri hills (Butler, 1918) but did not reappear for about 9 decades. Since 1961 (Srivastava, 1962), it has become an annual feature infecting both the summer and autumn crops. In the north-eastern part, late blight appear for the first time in 1883 at Darjeeling (West Bengal) and spread rapidly to the adjoining hills (Butler, 1903; Dastur, 1915). In the plains of West Bengal, it was first observed in 1898-1900 in Hooghly district and continued in severe form during the following two years (Butler, 1903). Later, it was not observed anywhere in the plains for about a decades. In 1913, it appeared at several places in Assam and Bihar (Basu, 1913, Dastur, 1917 and Dey, 1947). In the plains of Uttar Pradesh, disease was not reported till 1943 when disease outbreak was found at Dehradun and Meerut (Lal, 1949). In Punjab, the disease occurred annually from 1958 to 1963 except during 1961. In the plains of south India, it was observed in Karnataka during 1935, 1960 and 1961 (Srikantaiaya, 1962). In Gujrat, Madhya Pradesh and Andhra Pradesh, the disease was observed in traces in 1968 and in Rajasthan in 1958 (Dutt, 1979). Potatoes were growing continuously in Mahabaleswar Hills and other parts of Maharashtra but late Blight was observed there only in 1973 (Kadam et al., 1974). Afterwards in India, appearance of late blight disease is a regular feature with high disease severity in hills while in plains, disease severity is moderate to high depending upon climatic condition. Presently, it appears every year in the hills and once in 2-3 years in devastating form, in the plain.

2.3 Economic Importance of the Disease

Epidemics of late blight of potato caused by *Phytophthora infestans* have induced significant yield losses in the past and still a major threat to potato production. It appears in epiphytic form every year and the entire crop is killed before complete the full vegetative growth. The disease is more regular and severe in north-eastern hills where, weather conditions become congenital for the disease build up early in the season and prevail over a longer period. In Indo-Gangetic plains, it occurs in moderate to severe form but, occasionally assumes epiphytotic proportions. For example, in 1985-86 crop season the disease appeared early in the season i.e. 2^{nd} week of December and killed the crop prematurely leading to heavy loses ranging 20-25% in Punjab, 40-45% in Haryana, 15-50% in Uttar Pradesh and 5-10% in Bihar and West Bengal (CPRI, 1987). During the last few years, the disease has assumed serious proportion in the plain regularly. Losses have been enormous, especially in Uttar Pradesh, Haryana and Punjab where the crop was killed during the active bulking phase resulting in losses up to 80% (CPRI, 1999). Even blight resistant verities were attacked but losses were less (15-20%). Rao and Vareesh (1989) estimated yield loss due to late blight in case of rainfed potato. Losses in unsprayed plots were around 39%. Arora (1999) reported that, smaller tubers than larger ones were infected by *Phytophthora infestans*. The effect was enhanced when the haulms were cut at higher percentage of foliar infection. During 1998-99 cropping season in West Bengal, the appearance of the late blight disease was noticed in between $10\text{-}15^{th}$ of January, when disease severity (50%), tuber infection (20%) and crop losses (40%) were much lower in sprayed plots of susceptible cultivar as compared to unsprayed plots (80% disease severity, 40% tuber infection and 80% crop losses respectively). But on the other hand, in case of resistant cultivar, disease severity (5%), tuber infection (5%) and crop losses (5%) were very negligible in sprayed plots as compared to unsprayed one (10% disease severity, 5% tuber infection and 10% crop losses, respectively) (Singh and Shekhawat 1999).

During the post independence period, only susceptible potato cultivars were grown and at that time there was no resistant cultivars. Due to which, 20% yield losses during 1960-65, 40% during 1975-80, 65% during 1985-90 and 80% losses were noticed on susceptible cultivars in the plains of India. But after the introduction of resistant cultivars, gradually the amount of losses was declined (CPRI, 1999). The sudden change in disease profile has been due to the fluctuation in weather. If weather continues to play truant, newer late blight strategies based on host resistance and timely application of fungicides using accurate disease forecasts have to be adopted.

Losses due to the disease have been recorded in different parts of the country by several workers (Dutt, 1979). These range in 19-65% in Eastern Hills, 10-75% Eastern Plains (Dutt, 1979). With the release of widespread cultivated variety, Kufri Jyoti in early seventies, the losses due to the disease came down considerably. However, in mid eighties, resistance in variety Kufri Jyoti was eroded as a result losses have again increased. Tuber rotting caused by *Phytophthora infestans* was less in blight resistant variety, Kufri Jyoti as compared to susceptible variety. Rot was more in large and medium size tubers in clay soil and in low lying areas of field where drainage was poor (Dutt, 1980). However, Bhattacharyya et al., (1987) found that in crops sprayed with different fungicide tuber rot was non-significant. Tuber infection in both fungicide sprayed and unsprayed crop was very high (up to 8%) in variety Kufri Jyoti. Tuber losses in the plains is also on the rise.

Phukan and Baruah (1994) studied on the reaction behaviour of potato plants to infection by late blight fungus. He reported that, plant age, leaf maturity and position of leaves on the plant affected the rate of infection. Young plants were more susceptible than older one. A linear increase in the growth of lesions was seen from upper to lower leaves. Lesion growth was more vigorous when abaxial side of the leaf was inoculated than when the adaxial side was used. Chatterjee (1997) reported about outbreak of potato late blight appeared in major potato growing areas of West Bengal (Hooghly, Burdwan and other areas) during 1967 and 1980 due to continuous spell of cloudy and rainy weather for 3-4 days in late January and early February. Again, in the year of 1979-80 late blight of potato appeared in Coochbihar (Kholta and other places), Dhupguri and Falakata blocks in Jalpaiguri districts due to foggy and cloudy weather in the month of January. Under sub-tropical plains of West Bengal, a 30 year survey (1971-2001) in the major potato growing areas viz., Hooghly, Burdwan and Nadia revealed that, occurrence of late blight was regular but incidence and severity of the disease varied from 2 to 75% and 1.5 to 60% depending upon environmental condition of the year and type of variety grown. The disease appeared between 1st to 3rd week of January every year. Out of 30 years, the incidence (75%) and severity (60%) of the late blight disease were the highest in the year 1994-95. The incidence and severity were low (<50%) in 1989-90, 1990-91, 1993-94 and 1998-99 as compared to other years because of dry weather that prevailed during the cropping season (De and Basu, 2002).

2.4 Symptomatological Study of Potato Late Blight Disease

Butler (1903) stated that in Bengal the disease was known by different names. In Singur (Hooghly district) the blight was called ‘Dhasa’ or ‘Marka’ as the plants rots or dies. In Chanditola, it is named ‘Tipi’ as it forms a spot and in Nalika it is called ‘Topadhora’. It is also often known as ‘Marmaria’. Butler (1903) clearly described the symptom of the disease. Late blight affects all plant parts viz. leaves, stem and tubers. It appears on the leaves as pale green irregular spots, which subsequently enlarge and appear as water soaked lesions. The spots in the beginning are more localized on the tips and margins of the leaves. In moist weather, the spots enlarge rapidly with central tissue turning necrotic and dark brown or black. Often, the spots have a purplish tinge. On the lower side of the leaves, white mildew (cottony growth) ring forms around the dead areas. In dry weather, the water soaked areas dry up and turn brown. On stem and petioles initially light brown lesion develops and these become subsequently elongated often encircling the stem or petiole. Under favourable conditions, the whole vine may be killed and blackened and the disease spreads rapidly killing the entire crop within few days. The diseased and decaying plants give fetid odour that becomes more pronounced in severely attacked fields.

Tubers of susceptible cultivar are rapidly infected in the soil by spores that are washed from the blighted foliage with rain water. Initially the tubers show a shallow, reddish brown dry rot that spreads irregularly from the surface through the flesh. The affected tissue first becomes dry and firm with somewhat caramelized and sugary texture. Soft rots due to other pathogens often follow the late blight rot and completely destroyed the tubers. Under humid and cloudy weather the lesions on all parts show white mildew.

2.5 Potato Late Blight Disease Development and Spread

The pathogen is spread by air-borne sporangia which are formed on infected plants. Under conditions of moderate temperature (18-20^{0}C) and high air humidity (>90% RH), massive numbers of sporangia can be formed in an infected crop. The sporangia are usually released in the morning when the rising temperature causes a sharp decrease in the air humidity, which are then spread by air movements. Under moist conditions when the leaf surface is wet, the sporangia, finding a susceptible host surface, start the process of infection. The infection can take place either by direct infection by the sporangium itself or by indirect infection via the release of 5 to 10 motile zoospores per sporangium, which in turn can infect the host plant. The breaking point between direct and indirect germination appears to be around 15^0C. At germination the sporangia and zoospores from germ tubes and infect by the formation of appressoria and penetration pegs. After penetration, an infection vesicle is formed and the hyphae grow both inter- and intra-cellularly and develop haustoria to extract nutrients from within the cells of the host and thus destroy the plant tissue (Grenville-Briggs et al., 2005). After a latent period as short as three days (Flier and Turkensteen, 1999; Carlisle et al., 2002), new sporangia are formed and spread to infect new plants. The fast and efficient spread, infection and colonization of the host plant gives it the potential of destroying all above ground parts of the crop within a week (Anderson et al., 2009). Depending on when this happens in the crop development cycle, the result can be varying degrees of quantitative and qualitative yield losses. The potato tubers can also be infected if sporangia are rainsed off the hailm down into the soil (De-Bary, 1876; Lacey, 1965; Andrivon, 1995). Tuber infection will reduce the quality of thee harvest and if a large proportion of the tuber is infected, it can result in total crop loss (Fry, 1975). Another very important aspect of this fact is that infected tubers can function as sources of inocula for late blight epidemics the following season.

2.6 Environmental Factors Responsible for Potato Late Blight Disease Development

Moisture and temperature are the main factors favouring the development of potato late blight and these weather conditions are responsible for the geographical distribution to the disease. In Holland, Van Everdingen (1926) suggested that the blight might be expected to occur within 15 days of the development of four of the conditions namely (i) dew formation during a period of at least four night hours, (ii) night temperatures not below 10^0C, (iii) a mean cloudiness on the following day of at least 0.8 i.e. 80% of the sky overcast with clouds, (iv) a rainfall on that day of not less than 0.1 mm. Crosier (1934) made detailed studies on the effect of temperature and humidity on the blight pathogen. The sporangia developed on the blight lesions at a relative humidity above 91% and became abundant above 97%. These may be formed at a temperature range of 3^0C to 26^0C with an optimum of 18^0C to 22^0C. The sporangia may germinate to form zoospores at a temperature range of 6^0C to 15^0C (optimum

12^0C). The direct germination of sporangia may take place from 4^0C to 30^0C (optimum 25^0C). The zoospores germinate within 30 minute at 12^0C to 15^0C and the germ tube grow best at 21^0C. Thus cool (12^0C to 15^0C) and humid (above 91% relative humidity) weather with heavy dews or rains alternatively with warm (20^0C) moist period favour the rapid development of the disease. In England, Beaumont (1947) suggested two criteria necessary for blight to develop. These are (i) a minimum temperature of 10^0C and (ii) a relative humidity not falling below 75% for at least two days. There are difficulties in forecasting the occurrence of blight over large areas as the conditions vary from place to place. On the basis of the weather conditions, different systems have been developed to forecast outbreaks of blight (Malik et al., 1955).

In India, the rains are heavy and weather is cool during summer in the hills. The blight therefore occurs annually in these areas. However, the monsoon rains are received earlier in the eastern hills and the blight too occurs early in these hills. The monsoon moves from east to west in the Himalayas and for that reason the blight occurs later in the western Himalayas. In the plains, the weather is generally warm and dry and the blight occurrences are not a regular feature. But, whenever low temperature prevails and the humidity is high on account of rains or dew or irrigation, the blight appears. In most of the plateau areas, the occurrence of the blight has been limited by the high temperature. The blight periods in the different regions are connected with the temperature and humidity and these have been shown in Thermohygrograms prepared by Dutt (1964). These periods broadly indicate the time when the blight is normally expected. However, the growers have to carefully watch the weather and as soon as the favourable conditions developed the occurrence of blight may be expected and necessary control measures may be undertaken. The congenial conditions for appearance and build-up of the late blight are: 10^0C–22^0C temperature, humidity above 75%, frequent rains, cloudy or foggy weather (Deweille, 1964 and Bhattacharyya et al., 1983). Arora et al. (1987) reported that, the temperature and moisture relations obviously indicate that the disease will be most severe when the initial temperature are very low to allow formation of sporangia and their germination by zoospores and there is slight rise in temperature to help optimum growth of the germ tube and subsequent development of the mycelium in the host. Rainfall at the time of sporulation of the fungus on the foliage determines the level of tuber infection. Heavy and frequent rains when about 50% of the foliage is infected, cause maximum infection of the underground tubers. Bombawele et al. (1991) examined 10 biometeorological variables in Punjab. Only hours temperature >20^0C was consistently negatively correlated with *Phytophthora infestans* disease progress. Disease could be developed even in the absence of rain, where dew appeared to be the alternative source of moisture. Harrison (1992) considered the effects of temperature, humidity, precipitation, dew, wind, irradiation and others for the development of the late blight disease.

Starodub et al. (1993) developed models for forecasting the disease based on statistical analysis of standard meteorological observations to determine the date of the beginning of an epidemic and probability of disease outbreaks during the vegetative season. Modelling for prediction of potato late blight considering meteorological elements was described, by Ahn et al. (1994). Meteorological data, obtained for the duration of the survey, was processed and applied in the 'BLITECAST' method to predict the occurrence and progress of potato late blight.

Effect of environmental factors on the development of late blight disease of potato in Assam was studied by Phukan (1995). In field plots planted with inoculated tubers, infection by *P. infestans* appeared much earlier than in plots with healthy tubers. Light rain, low temperature and high relative humidity prevailing within the plant canopy favoured spread of the disease. Once the disease appeared in the crop, the process of infection continued until most of the plants were destroyed. Ahn et al. (1998) developed a new method for prediction of initial appearance of potato late blight. The method is called 'moving average method'. In this method, the disease was expected to occur after 1-2 weeks if 2 meteorological conditions, relative humidity >79% of 5 day and air temperature >12^{0}C of 7-day moving average, were consecutive for 7 days. Both the 'BLITECAST' system and the 'moving average method' appeared to accurately predict the date of initial development of late blight and the accuracy of prediction was 92.3% in both system. Saucedo et al. (2002) reported that, the foliar microclimate also influenced the progress of late blight in potato crop. The foliar microclimate (temperature and relative humidity) differed between cultivars with different growth habits. The values of temperature and relative humidity permitted forecasting of disease incidence. Fahim et al. (2003) described the relationship between climatic conditions and potato late blight epidemic in Egypt during winter seasons in 1999-2001. An indicator variable for the occurrence of outbreak during the season based on the number of favourable days in terms of temperature and relative humidity during November to January was used to describe the disease status throughout the tested period. Weather conditions prevailing during potato-growing winter seasons were studied and infection efficiency, a function of the environmental conditions and the potato cultivars, was calculated.

2.7 The Integrated 3S Technology of Information Communication Technology (ICT) for Disease Monitoring and Management

The term, 3S technology, refers to Remote Sensing, geographical information system (GIS) and global positioning system (GPS). Information management in a geographic perspective is key to improving farm practices in agricultural systems as it is inherently spatial. Agricultural systems are characterized by heterogeneity as a result of biological and physical aspects that triggers occurrence and distribution of plant pathogens and disease. Plant disease management practices can be improved by putting epidemiological information onto landscape and weather surface in the same format as other field information using a geographic information system (GIS). In the case of infectious disease the study of their geographic distribution frequently involves examining the diffusion of the disease through space over a given period of time (spatio-temporal mapping and analysis). Spatio-temporal analysis of disease epidemiology is concerned with cluster validation, e.g., that a detected cluster is not due to mere chance factors, and with attribution of detected clusters to the appropriate factors that played a role in their occurrence. Analysis also includes doing comparisons with other relevant patterns/clusters (in the same place at different times and in other places) and again trying to methodically explain any spotted differences or trends. This geography plays a key role to explore the distribution and spread of disease and risk taking behaviours. Although the mapping of disease data can be relatively straightforward, interpreting spatially referenced disease data can sometimes be challenging, particularly for non-infectious diseases. Disease Geography utilizes a wide variety of pathological, terrestrial and weather data in synoptic scale to look for strong correlations between diseases and environmental factors. Understanding geographic patterns of disease and its diffusion / spread helps in informed decision making. The geographic study of disease, patterns of mortality, and other preventive issues are useful when it reveals unusual distributions that can be further investigated and confirmed or refuted by appropriate epidemiologic and other studies.

2.7.1 Application of Remote Sensing Technology for Disease Detection and Monitoring

The most practical, objective and cost-effective way to monitor vegetation and identify spectral anomaly is from a local to global scale is the use of Earth Observation technologies. Satellite can provide local to global coverage on a regular basis. They also provide information on remote areas where ground measurements are impossible on a regular basis. Different sensors are currently onboard Earth Observation satellites that may be applicable to the monitoring of vegetation water content. Reflectance of agriculture crops in the visible and infrared regions have been studied by several researchers in order to estimate different crop properties and to assess growth status of the crop (Carter and Knapp 2001; Kumar et al., 2001; Yang and Chen 2004; Yang et al., 2007). Green leaves typically display very low reflectance and transmittance in visible regions of the spectrum (400 to 700 nm) due to strong absorptance by photosynthetic and accessory plant pigments (Chappelle et al., 1992). There is a slight increase in reflectivity around 550 nm (visible green) because the pigments are least absorptive there. In contrast, reflectance and transmittance are both usually high in the near-infrared regions (700 to 1300 nm) because there is very little absorptance by sub-cellular molecules or pigments and consequently high scattering at the interfaces of mesophyll cells (Gausman, 1974; Gausman, 1977). This sharp dissimilarity in reflectance properties between visible and NIR wavelengths underpins a majority of remote sensing approaches for monitoring and managing crop and natural vegetation communities (Knipling, 1970).

Under conditions of pest and disease infestation, decrease in NIR values related to a decline in plant vigor and canopy cover and an increase in PAR related to chlorophyll absorption are commonly observed (Knippling 1970; Lorenzen and Jensen 1989; Yang et al., 2007). Decreases in leaf area and foliage density and changes in leaf orientation and canopy architecture caused by necrosis, discoloration and leaf breakdown of infested plants are reflected by smaller NIR and larger PAR reflectance values (Knippling 1970; Nilsson 1985a; Steven et al., 1990). A flattening of the spectrum in the visible region and a decrease of the NIR shoulder plateau near 800 nm were observed in a fungi-infected field bean crop (Malthus and Madeira et al., 1993), and disease sensitivity peaks near 485 and 675 nm were identified in blast-infected rice (Kobayashi et al., 2001). These studies show the potential use of spectral reflectance measurements in quantifying the incidence or severity of plant diseases. Using spectral reflectance Yang et al. (2009) tried to estimate the status of crop growth in relation to infestations with plant diseases and pests is also suitable for developing sensors for site-specific agricultural applications.

The use of remote sensing for crop disease assessment started many decades ago. In the late 1920s, aerial photography was used in detecting cotton root rot disease (Taubenhaus et. al., 1929). In the early 1980s, Toler et al. (1981) used aerial colour infrared photography to detect root rot of cotton and wheat stem rust. Reflectance data was found to be capable of detecting pathogen-induced biophysical changes in the plant leaf and canopy. When crop plants are stressed, such as by disease, their absorption of incident light changes in the visible range and in the NIR range (Carter and Knapp, 2001; Adams et al., 1999; Dawson and Curran, 1998; Lichtenthaler et al., 1996; Gitelson and Merzlyak, 1994; Guenther, 1990). This reaction is probably due to the decreased chlorophyll content, changes in other pigments, and foliar internal structure. The change of absorption consequently influences the reflectance of stressed plants. Healthy crops appear green since the green light band (550 nm) is reflected relatively efficiently compared to blue, yellow, and red bands, which are absorbed by photoactive pigments. Diseased crops usually exhibit discrete lesions on leaves, corresponding to necrotic or chlorotic regions, which increases reflectance in the VIS range, especially in the chlorophyll absorption bands. In particular, reflectance changes at wavelengths around 670 nm causes the red edge (the sharp transition in the reflectance spectrum from low VIS reflectance to high NIR reflectance that generally occurs around 730 nm) to shift to shorter wavelengths. Conversely, biomass reduction linked to senescence, reduced growth, and defoliation decreases the canopy reflectance in the NIR band. Therefore, by comparing the spectrum difference of stressed and healthy plants, theoretically, we are able to identify the stress severity of green vegetation. Many studies have examined the relationship between chlorophyll content and spectral reflectance in visible and NIR ranges (Carter et al., 1996; Datt, 1999; Gitelson and Merzlyak, 1996; Knapp and Carter, 1998). However, most of these studies were based on leaf spectral reflectance and very few were on canopy light response (Gitelson and Merzlyak, 1996). Some of the other diseases identified through remote sensing techniques include wilt disease of coconut, potato late blight, bunch disease of pecans, phony disease of peaches, southern corn leaf blight, bacterial blights and root rot in field beans, spreading decline of citrus, halo blight of dwarf beans, root rotting fungal disease of cereals, etc.

Modern sensors have superior spatial, spectral and radiometric resolutions, thereby offering enhanced capabilities to detect and map disease symptoms. The presence of disease in crops can alter its reflectance properties. In the visible (VIS) wavelengths (~ 400nm to 700nm), the reflectance of healthy vegetation is relatively low due to strong absorption by pigments. If affected by disease the reduction in pigment activity causes an increase in VIS reflectance. Vigier et al. (2004) found that the red wavelengths contributed the most in the detection of sclerotinia stem rot in soybeans. On the other hand, the reflectance of healthy vegetation in the near-infrared (NIR) region (~700nm to 1300nm) is significantly high. With a disease that damaged the leaves (e.g. cell collapse), the reflectance in the NIR region is expected to be lower. For stress in tomatoes induced by a late blight disease, it was found that the NIR region was much more valuable than the VIS range to detect disease (Zhang, et al., 2002). Furthermore, in the shortwave infrared (SWIR) range (~1300nm to 2500nm), the spectral properties of vegetation are dominated by water absorption bands. Less water on leaves and canopies will increase reflectance in this region. Apan et al. (2004) noted the key role of the SWIR bands in the discrimination of healthy and diseased (orange rust) sugarcane crops.

With the rapid development of remote sensing technology in recent decades, hyperspectral remote sensors, such as airborne visible infrared imaging spectrometer (AVIRIS), compact airborne spectrographic imager (CASI), multispectral infrared and visible imaging spectrometer (MIVIS), and hyperspectral mapping system, are now available to agricultural applications. These sensors can provide quality images with high spatial and spectral resolutions required for precision agriculture (Taranik et al.,1993; Fraser, 1998; Bianchi et al., 1999). Hyperspectral Remote Sensing is a technique that utilizes sensors operating in hundreds of narrow contiguous spectral bands, offers potential to improve the assessment of crop diseases. The reflectance and absorption features in narrow-bands are related to specific crop physico-chemical characteristics, such as biochemical composition, physical structure, and water-content (Strachan et al., 2002). Several studies have shown that use of hyperspectral data makes significance improvements in detecting plant stress (Carter 1998), identifying small differences in the percentage of green vegetation cover (McGwire et al., 2000), variation in crop moisture (Pen˜uelas et al., 1995), and the classification of land cover types (Janetos and Justice 2000). However, analysis of the large number of bands from hyperspectral sensors is complex and time consuming and needs special algorithms to select an optimum set of bands for the required study (Ray et al., 2006). Data acquired from such sensors may allow the capture of specific plant attributes (e.g. foliar biochemical contents) previously not detectable with broadband sensors. Because of the high spectral resolution with a narrow band range of about 10 nm or finer, hyperspectral remote sensing images produce a complete spectrum for each pixel within the scene. These characteristics combined with high signal-to-noise ratio enable us to differentiate various vegetation stresses based upon spectra of small patches of ground surface (Rush, 2002; Lelong et al., 1998). Late blight, caused by the fungal pathogen *Phytophthora infestans*, is a disease that spreads quickly in potato fields in suitable weather conditions during growing season. Conventional ground scouting was not economic to provide the efficient detection and monitoring in a large potato cropping area. Remote sensing, however, can provide a powerful technology to collect crop canopy data that can be used to analyze the geo-temporal and geo-spatial properties of the biological features of the crop canopies, including the symptoms of late blight.

Zhang et al. (2003) developed an approach including the minimum noise fraction (MNF) transformation, multi-dimensional visualization, pure pixels endmember selection and spectral angle mapping (SAM) to process the hyperspectral image for identification of diseased tomato plants. The 28 signal eigenimages were used to generate a multi-dimensional visualization space for endmember spectra selection and SAM. Classification with the SAM technique of plants spectra showed that the late blight diseased tomatoes at stage 3 or above could be separated from the healthy plants while the less infected plants (at stage 1 or 2) were difficult to separate from the healthy plants. The results of the image analysis were consistent with the field spectra. The mapped disease distribution at stage 3 or above from the image showed an accurate conformation of late blight occurrence in the field. Yang et al. (2007) studied brown plant hoppers and leaf-folder infestations in rice plants. The infested conditions of the plants were ranked and efforts were made to identify the extent of infestations using spectroscopic reflectance (350–2400 nm) data collected under field conditions. The results indicated that the spectral range from 426 to 1450 nm showed the maximum correlation intensity. The changes in spectral properties were low in visible and ultraviolet (UV) range, whereas the infrared region (740–2400 nm) yielded the maximum change in spectral signature.

Ray et al. (2011) investigated the utility of hyperspectral reflectance data for potato late blight disease detection using hand-held spectroradiometer over the spectral range of 325–1075 nm. The notable differences in healthy and diseased potato plants were noticed in 770–860 nm and 920–1050 nm range. Several vegetation indices were calculated and notable differences were found at different levels of disease infestation in potato plants. To discriminate the disease affected potato plants from healthy one the optimal hyperspectral wavebands were identified. Different disease symptoms affect the optical properties of plants in the following spectral regions: pathogen propagules in the VIS (depending on the pathogen); chlorophyll degradation (necrotic or chlorotic lesions) in the VIS and red-edge (550 nm; 650–720 nm); photosynthesis disturbance as fluorescence (450–550 nm; 690–740 nm) and in the TIR (8000–14000 nm); senescence in the VIS and NIR (680–800 nm) due to browning and SWIR (1400–1600 nm and 1900–2100 nm) due to dryness; changes in canopy density and leaf area in the NIR; and changes in the transpiration rate in the TIR (8000–14000 nm).

Apan et al. (2004) used discriminant analysis to determine which narrow band indexes based on Hyperion data were the best indicators of plant stress caused by the "orange rust" disease in sugarcane. They found that indices taken from the red edge spectra were poor indicators of disease. Indices using only NIR wavelengths performed moderately better. The best indices were those using the 1600 nm short wave infrared band in a ratio with either an 800 nm NIR band or 550 nm green band. The best results for the detection of diseases to be obtained in the VIS and NIR range of the spectrum. Steddom et al. (2003) showed that multispectral disease evaluation can be effectively used to measure necrosis caused by Cercospora leaf spot in sugar beets. A detection of rhizomania in sugar beet fields was also feasible (Steddom et al., 2003). Using a quadratic discriminating model based on reflectance, Bravo et al. (2003) showed the classification results of yellow rust infestation on winter wheat with a accuracy of 96%. Yellow rust decreases the chlorophyll *a* concentration, which leads to an increase in canopy reflectance in the VIS range and a decrease in the NIR.

A significant challenge for agricultural remote sensing applications is to be able to separate spectral signals originating with a plant response to a specific stress from signals associated with normal plant biomass or the background "noise" that is introduced by exogenous non-plant factors.

2.7.2 Application of Geographic Information System for Disease Monitoring and Management

Geographic Information Systems (GIS) are, in the broadest sense, manual or computer based sets of procedures that permit users to input, store, retrieve, manipulate, analyze and output spatial data referenced by geographic coordinates. It has the ability to integrate layers of spatial information generated at various scales onto a common platform and to uncover possible relationships that would not otherwise be obvious. Besides maps and satellite data GIS can integrate the data collected by Global Positioning System (GPS) receiver. When a variety of data is registered to the same coordinate system, the possibilities for sharing data and creatively analyzing the spatial relationships increases dramatically. Two main forms of data formats are supported by GIS viz. vector and raster. In vector data sets, geographic entities are represented as points, lines, and polygons their attributes are stores in a relational database. In raster data sets, the data are organized as a matrix of grids or lattice or pixels referenced spatially by row and column position. Most of the surfaces are better represented by raster grids viz. digital elevation model, air pollution etc.

It is relevant in disease modelling as every epidemiological disease has spatial components. The aim is to find spatial relationships of landscape features that interact with the progress of an epidemic to refine cultural management strategies for plant disease control. Most of the disease patterns are associated with one or at most a few environmental factors. The ability of GIS to utilize simultaneously numerous strata of data from a variety of sources suggests that GIS should be an appropriate tool for analyzing complex spatial patterns of diseases in which a multitude of factors may interact. If the spatial distribution of a disease is well characterized and data for specific environmental risk factors exist, GIS may be applied in a fairly straightforward manner to show the distribution of the disease, to identify other likely sites of infection, and to provide a useful visual representation for managers designing means of providing in near real time data that can be used, viz. to forecast geographic patterns of crop disease outbreaks. It has been critical in developing planning scenarios and decision models involving spatial data. The multi-sensor data and GIS technology offers the opportunity to integrate vast amounts of environmental data from satellite borne sensors into major control and intervention efforts. The GIS models could be categorized into different forms viz. Empirical models, Capability vs Suitability models, Statistical models and Black-box models.

A more complex use of GIS in disease epidemiology would involve a GIS modeling component that might be used to predict changes in the distribution of disease. Many standard epidemiological models for studying the growth of epidemics have been developed but relatively few explicitly model the spatial pattern of disease dynamics. GIS, in principle, could provide this capability. Ancillary data on source of seed potato, time of sowing, seed treatment, proximity to water sources, alternate host, cropping pattern and epidemiology along with synoptic weather and vegetation bio-optical properties can augment modelling the initiation and spread of the PLB. These models might be combined with diffusion models, locally, to predict patterns of disease transmission. With a properly designed surveillance system, it would be possible to monitor changes in disease prevalence. However, GIS is of little practical value when a spatial pattern is uniform. On the other extreme, if the change in pattern is faster than data can be acquired, spatially referenced data might be skewed and misleading.

2.7.3 Application of Global Positioning System for Disaese Monitoring and Management

GPS receivers determine location based on a system of navigation satellites (constellation) that broadcast signals containing time and position information. GPS receivers on the ground collect the satellite signals and determine position in a spherical coordinate system such as latitude and longitude or a planar coordinate system such as the Universal Transverse Mercator system common on terrestrial maps. The planar coordinate system is capable to calculate distance and direction in a two-dimensional Euclidean system. Such calculations are required for geo-statistical analyses. Elevation can be added if three-dimensional spatial considerations are important. With a single channel hand held receiver the expected positional accuracy can be in the range of 15 to 25 m. On the other hand Differential GPS (DGPS) can provide location accuracy to about 2 m but obviously cost prohibitive. In DGPS system two receivers are used simultaneously, one is at base station whose position is known and the second is rover station whose position to be determined with the help of base station to correct for source error.

The ICT components viz. remote sensing, geographic information system, global positioning system along with geostatistics can be used to advantage at different levels of management and expertise. A field person equipped with hand held GPS unit could relay the coordinates of a plant disease location along with detailed description about the disease severity, diffusion etc., to a RS-GIS lab equipped with software, hardware and multi-speciality team of specialists can generate various scenario and support decision making process at higher level. Simple overlaying of disease reporting points on other ancillary data viz. landscape characteristics associated with the disease (presence of alternate hosts, watercourses etc), roads, digital elevation models, hydrography, land ownership boundaries, and most importantly, other agricultural data can dramatically increase the disease perception and sufficient to characterize disease / pest problem and to uncover possible relationships that would not otherwise be obvious. Spatially located field observations of incidence combined with satellite borne weather data products at suitable temporal and spatial scale can be used effectively for modelling of wind borne dispersal of several fungal diseases and recurring regional pattern over the years and integrated pest management. Through an iterative process of comparing spatial data on risk with observed incidence, our understanding of the spatial and temporal aspects of disease processes should improve along with our ability to produce maps useful to farmers and generate control strategy. The plan involved a risk assessment procedure and mitigation of risk immediately surrounding fields based on disease observations. GIS and Geostatistics are particularly useful in identifying recurring patterns of plant disease, as well as other problems such as insect and weed infestations. The association of environmental factors, landscape features, and cropping patterns with the recurrence of disease or other problems can be readily communicated to key managers and decision makers. The integration of GIS, GPS, and Geo-statistics provides a tool for the refined analysis of traditional and contemporary biological/ecological information on plant diseases.

2.8 Estimation of Disease Severity

Disease severity is the absolute or relative area of the disease affected sampling leaf of plant which is normally expressed as a proportion or percentage (Nutter et al., 1991). Measurement of disease severity is so much important for assessing the epidemiological models useful for predicting yeild losses in food crops. The quantification of disease severity is basically important for rapid management decisions related yield loss and to estimate resistance of plant to apply fungicides or pesticides in a proper cost-effective manner. From last few decades, so many procedure has been used by several researchers to estimate the disease severity. But most of disease severity estimation methods are either subjective or qualitative which do not fulfil the proper requirements for quantitative estimation of disease severity. Accurate disease severity measurements are necessary to determine crop loses due to disease.

There are a number of ways to measure the actual disease severity and statistical method is one them. Many statistical methods exist to assess agreement with actual values and investigate reliability (Madden et al., 2007; Nutter and Schulz, 1995). Some of those are standard statistical tools which is widely used in plant pathology. Disease assessments of *Stagonospora* leaf spot on orchardgrass was analyzed by Sherwood et al. (1983) using two- and three-way ANOVA to identify factors affecting disease assessment and the results showed that there were significant effects of lesion number, leaf size, individual rater and rater experience apart from the actual disease. To test the reliability and general agreement of rater estimates and measurements, ANOVA has been used to calculate the intra-class correlation coefficient (ρ). The ratio of actual variance to total variance can be presented as intraclass correlation coefficient (Shokes et al., 1987; Nita et al., 2003; Madden et al., 2007). Shokes et al. (1987) studied the correlation analysis to show improvement in repeat assessments, and to identify the more reliably estimated indicators of disease severity. Another well-known statistical analysis tool is regression analysis which has been used to investigate various aspects of error in disease assessment (Bock et al., 2008b) and reliability, precision and accuracy of estimated or measured data (Guan and Nutter, 2003).

During the last few decades, most acceptable precision and accuracy of visual disease assessments have often been achieved using conventional disease scales. The identification of visual symptoms is most important for diagnosis of diseases affected plants. Visual assessment of disease can be categorised in two category. One is pictoral descriptive keys that show plants with varying amount of types of disease symptoms and another one is standard area diagrams (Lindow, 1983). Pictoral descriptive keys for assessing disease severity are exemplified by those used for assessing late blight of potato (Ullstrup et al., 1945). Such visual disease assessment keys can be assessed by single observers to estimate the plant disease severity with different environmental conditions or cultural procedures (Sherwood et al., 1983). In standard area diagrams, assessed disease affected plants with known and graded amounts of disease using pictoral representation are compared with disease plants to allow estimation of disease severity (James,1974). Some new key-based scales for various crops has been developed by the BMS (British Mycological Society) committee which were useful to plant disease assessment, specially to assess late blight of potato (Anon., 1947) that bore some apparent similarity to the Horsfall-Barratt scale (Horsfall and Cowling, 1978). After that, to measure disease severity different types of rating scales has been developed with continuous or discrete variables (Sheskin, 1997). Visual plant disease assessment scale can be categorized as nominal or descriptive scales (Chester, 1950), ordinal scales (Newell and Tysdal, 1945), interval or category scales (Cobb, 1892), and ratio scales (James,1974). To asses the late blight disease severity of potato in the field, interval or category scale was widely used. A unique type of interval scale based on percent severity (for example, 0.1, 1.0 2.0, 5.0%. . . 100%) was used to assess late blight of potato in Great Britain (Anon, 1947). Field keys are used in conjunction with a descriptive or diagrammatic portion of the scale that offers explanation as to the likely distribution/ frequency of the symptom in the field or on plants, which contains quantitative information (Anon, 1947). The late blight type key was generally used on a whole field basis and apparently received wide usage (Chester, 1950).

Perception based visual disease assessment are too much subjective. Visual disease severity estimation is so much error prone and can be differ significantly from the true amount of disease (Sherwood et al., 1983). Modern technologies offers great opportunity to assess plant disease severity with high reliability, precision, and accuracy. One of these, visible light photography and digital image analysis techniques has been gradually increased in last three decades with the help of sophisticated and user friendly analysis software (West et al., 2003). By contrast, remote sensing technology is the most recent noncontact techniques with vast potentially discerning opportunities for application in measurement of plant disease severity.

When plants are affected by pathogen, the complex molecular mechanisms of plants struggle to defense it. At the primary stages, when visual symptoms of disease is not present in the leaf surface, physiological mechanism of plants reduce their performance due to pathogen (West et al., 2003) and at later stage, chlorophyll content of leaf reduced which increase reflectance in the VIS and cause a shift of the rededge position in the spectrum. Due to the decrease of water content in leaves as well as decrease of canopy density and leaf area for the disease infection, reflectance of canopy spectrum decrease in NIR region (Franke and Menz 2007). Plant disease monitoring using remote sensing can be classified in three category such as detection (deviation from healthy), identification (diagnosis of specific disease symptoms among others), and quantification (measurement of disease severity, e.g., percent leaf area affected) (Mahlein et al., 2012a). Remote sensing observation for disease assessment are strongly associated with observation scale (Woodcock and Strahler1987). Remote sensing upscalling approach and spatial patterns (heterogeneity/homogeneity) of disease phenomena is crucial for operational disease assessment. To perform this procedure three scales of observation can be identified: (i) the single leaf scale which is mainly used to test the laboratory based methodology/algorithms (Lins et al., 2009; Zhang et al., 2014; Stilwell et al., 2013; Huang et al., 2012; Yuan et al., 2014) (ii) the plant scale which is usually performed for pest management applications and in-situ precision farming (Okamoto et al., 2007; Mirik et al., 2006; Moshou et al., 2004, 2005) (iii) the spatilized scale which can cover an entire field by exploiting airborne data (Zhang et al., 2003), unmanned aerial vehicle (UAV) or a region, by using satellite sensors (Mirik et al., 2011, 2013).

Remote sensing sensor system can be classified into nonimaging and imaging sensor-based applications. Nonimaging sensors are spectroradiometers (handheld or mounted on any platform) and fluorescence radiometers. Widely used imaging sensors include visible or infrared RGB cameras (visible or infrared), multispectral and hyperspectral sensors, thermal infrared sensors, and fluorescence imaging sensors. To disease detection and measure the disease severity, spectral response of disease affected plants acquired by handheld spectroradiometers, airborne, and satellite-borne sensors can be processed by using data mining algorithms. Hand held spectro-radiometer data in conjunction with airborne and spaceborne hyperspectral data are being widely used for detecting plant stress (Carter, 1988), crop moisture variation (Pen˜uelas et al., 1995) as well as disease detection and monitoring. Spectral characteristics of rice plants affected by brown plant hopper (Nilaparvatalugens) at different severity level was investigated by Yang and Cheng (2001) who have shown significant differences in reflectance at wavelengths of 755 and 890 nm. Bravo et al. (2003) have classified of yellow rust infected wheat plants and healthy plants by using hyperspectral and quadratic discriminating model. Zhang et al. (2003) developed a MNF approach to discriminate the late blight (*P. infestans*) disease affected tomato plant from the healthy one by using hand-held spectrometer data. The classification results successfully separated the diseased tomato plants at 3 severity level. Ray et al. (2011) investigated the sensitive narrow bands of using hyperspectral indices to differentiate healthy and PLB disease affected potato crops. By using the spectral derivative method it was able to differentiate the disease affected potato crop spectra according to the PLB disease severity. Jones et al. (2010) studied reflectance spectroscopy of ultraviolet, visible and NIR to quantify the disease severity of *Xanthomonasperforans* affected tomato leaves and found that the wavelength region of 750–

760 nm was highly sensitive to the disease. Hamid Muhammed and Larsolle (2003) assessed fungal disease severity in a wheat crop by using feature vector-based analysis and found high correlation in between estimated and the corresponding field assessments of disease severity. Mahlein et al. (2012b) studied to analyse sugar beet diseases specifcally *Cerospora* leaf spot, powdery mildew and leaf rust in the spectral range of 400–1000 nm to monitor the diferent stages of disease severity. As a result the leaves were classified successfully as healthy or diseased with different severity level. Recent remote sensing techniques offers good perspectives for operational implementation of disease severity estimation rather than traditional techniques. Low cost remote sensing data acquisition with high spectral and spatial resolution enhance the operational capabilities at large scale. Sugiura et al. (2016) investigated a new potato late blight disease severity estimation technique in a field using RGB imagery from an unmanned aerial vehicle (UAV). As a result disease severity estimation method was established using an image processing protocol and errors of severity estimation was found so nominal rather than the visual estimation technique. Satellite remote sensing method is most useful to determine the disease severity in regional scale. To detect winter wheat stripe rust multiscale capabilities (from leaf-to-satellite observation) of remote sensing was discussed by Wang et al. (2012). Dutta et al. (2014) studied the spectral response of healthy and late blight affected potato crops using vegetation indices and showed a large difference between their profiles.