

आलू के पछेती झुलसा (फाइटोफथोरा इन्फेस्टैन्स (मोंट.) डे बैरी) रोग के लिए
मौसम आधारित पूर्वाभास मॉडल

**Weather based forewarning models for potato
late blight (*Phytophthora infestans* (Mont.) de
bary) incidence**

Deepti Joshi



**DIVISION OF AGRICULTURAL PHYSICS
ICAR-INDIAN AGRICULTURAL RESEARCH INSTITUTE
NEW DELHI - 110012**

2022

**Weather based forewarning models for potato late blight
(*Phytophthora infestans* (Mont) de bary) incidence**

A Thesis

By

Deepti Joshi

**Submitted to the Faculty of Post-Graduate School,
ICAR-Indian Agricultural Research Institute, New Delhi
in partial fulfilment of the requirements
for the award of the degree of**

**MASTER OF SCIENCE
IN
AGRICULTURAL PHYSICS**

2022

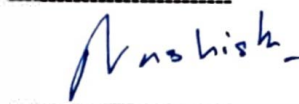
Approved by:

Advisory Committee

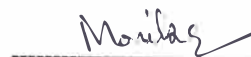
Dr. (Mrs.) P. Krishnan (Chairperson):



Dr. Ananta Vashisth (Co-Chairman):



Dr. Monika Kundu (Member):



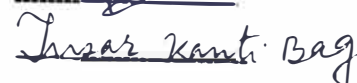
Dr. Mahesh C Meena (Member):



Dr. Amrender Kumar (Member):



Dr. Tusar Kanti Bag (Member):





Division of Agricultural Physics
ICAR-Indian Agricultural Research Institute
New Delhi-110012, India



Dr. (Mrs.) P. Krishnan
Head and Principal Scientist

CERTIFICATE

This is to certify that the thesis entitled, “**Weather based forewarning models for potato late blight (*Phytophthora infestans* (Mont.) de bary) incidence**” submitted to the Faculty of Post Graduate School, Indian Agricultural Research Institute, New Delhi, by **Ms. Deepti Joshi**, Roll No. 21415 in partial fulfilment of the requirements for the award of the degree of **Master of science in Agricultural Physics**, is a record of bonafide research work carried out by her under my guidance and supervision and that no part of the thesis has been submitted anywhere for the publication or for any other degree or diploma.

I further certify that the assistance and help received during the course of this investigation have been duly acknowledged.

Place: IARI, New Delhi

Dated:

(P. Krishnan)

Chairperson
Advisory Committee

**DEDICATED TO MY
GRANDFATHER,
PARENTS, BROTHER AND
MY CHAIRPERSON**

ACKNOWLEDGEMENT

At the very outset, with folded hands, I bow my head with reverence and dedicatedly accord my gratitude to the “Almighty”, the most merciful, the most gracious and compassionate whose grace, glory and blessing gave me the courage in odd critical times for the successful completion of this degree.

*I wish to express my deepest sense of respect, faithfulness and profound sense of gratitude to **Dr. (Mrs.) P. Krishnan**, Head and Professor, Division of Agricultural Physics, as Chairperson of my Advisory Committee for her invaluable guidance, constant encouragement, scholarly suggestions, untiring enthusiasm, affectionate behaviour, useful discussion and peerless criticisms during the course of investigation and preparation of the manuscript. Her kind-heartedness and devotion left an enduring impression in my mind.*

*I express my profound thanks to **Dr. (Mrs.) Ananta Vashisth**, Principal Scientist and Co-Chairman of the Advisory Committee for her concrete suggestions and commendable help throughout the experimental period. I convey my respectful sincere thanks to **Dr. (Mrs.) Monika Kundu**, respected scientist of the Division of Agricultural Physics for her help during my research work and academics from time to time during the course of my MSc. programme.*

*It is a great privilege for me to express my esteem and profound gratitude to **Dr. Vinay Kumar Sehgal**, Principal Scientist, of the Division of Agricultural Physics, for his cooperative attitude, constructive and valuable suggestions and help throughout the programme of this work.*

*I convey my respectful and sincere thanks to the members of my Advisory Committee, **Dr. Mahesh C Meena**, Soil Science and Agricultural Chemistry, **Dr. Amrender Kumar**, Agricultural Knowledge Management Unit, **Dr. Tusar Kanti Bag**, Plant Pathology, Indian Agricultural Research Institute, New Delhi, for their concrete suggestions and commendable help throughout the experimental period.*

*I sincerely acknowledge the help and support by **Mr. Rishabh** in my calculation work.*

It gives me an immense pleasure to extend my sincere thanks to the entire scientists' community of the Agricultural Physics Division. I

gratefully acknowledge the valued opinion and help rendered by my seniors and candid thanks to all my friends and juniors.

*I am extending my sincere gratitude to technical, administrative and supportive staff members of the Division of Agricultural Physics, IARI especially to **Mrs. Vipin mam** and **Usha mam**, for their support which helped me to complete my degree program in the division.*

*I express my deep sense of gratitude to all my seniors of the division especially **Sona sir**, **Priya mam**, **Alka mam**, **Sujan sir**, **Shreya mam**, **Aatralarasi mam**, **Koushik sir**, **Tridiv sir** and **Nandita mam** and my batchmates **Sudipta**, **Bhavya**, **Abhilasha** and **Debjyoti** for their support, suggestions and company during these months.*

*I express my sincere gratitude to **Nilesh sir** who was very helpful and supportive throughout.*

*The endless love, affection, sacrifice and constant inspiration from my Dadaji, mummy, papa and Bhai has enabled me to reach the footstep of my long-cherished aspiration. A heartfelt thanks to my close friends **Diksha**, **Anjali**, **Ananya** and **Anupam** who have been the pillars of my strength, for having faith in me and encouraging me in all endeavours.*

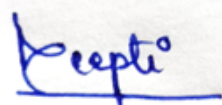
*I would like to express my sincere thanks to my friends **Anand**, **Mallikarjun**, **Roopam**, **Gauri** and my roommate **Karishma** and hostel mates **Tanvi** and **Resham** with whom I have shared this journey and lived a homely life in hostel, their spiritual bliss and unbound affection assisted me throughout.*

Fellowship received from IARI during the study is duly acknowledged.

It's tough to compile and thanks to all the people that came along my way during this journey however, starting from our hostel security guards to mess servants to divisional staff, everyone was always kind and supportive to me. All may not be mentioned but none is forgotten. Words may be due, but thoughts will remain with me.

Date:

Place: IARI, New Delhi



Deepti Joshi

CONTENTS

Chapter No.	Title	Page No.
1.	Introduction	1-4
2.	Review of Literature	5-29
3.	Materials and Methods	30-41
4.	Results	42-119
5.	Discussion	120-128
6.	Summary and Conclusion	129-132
7.	Abstract (English) and	133-134
8.	Abstract (Hindi)	135-136
9.	Bibliography	137-146

LIST OF TABLES

Table No	Title	Page No
2.1	Models developed for forecasting late blight of potato and their specifications	22-25
3.1	Simple and weighted indices used in models using composite weather variables	35
4.1	Correlation of late blight disease parameters of potato crop with weather parameters (from 2006 to 2020), at two locations	47
4.2	Weather based prediction of disease severity for early planting by different models for Srinagar	50
4.3	Equations for disease severity prediction of early planting for Srinagar location	51
4.4	Weather based prediction of disease severity for normal planting conditions by different models for Srinagar	52
4.5	Equations for disease severity prediction under normal planting conditions for Srinagar location	53
4.6	Weather based prediction of disease severity for late planting by different models for Srinagar	54
4.7	Equations for disease severity prediction under late planting conditions for Srinagar location	54
4.8	Weather based Prediction of disease severity for all plantings (pooled data) by different models for Srinagar	56
4.9	Equation for disease severity prediction of all plantings (pooled data) for Srinagar location	57
4.10	Weather based prediction of disease severity under early planting condition by different models for Kalyani	58
4.11	Equation for disease severity prediction under early planting conditions for Kalyani location	59
4.12	Weather based prediction of disease severity under normal planting conditions by different models for Kalyani	60
4.13	Equation for disease severity prediction under normal planting conditions for Kalyani location	60
4.14	Weather-based prediction of disease severity for late planting by different models for Kalyani	62
4.15	Equations for disease severity prediction of late planting for Kalyani location	62
4.16	Weather based prediction of late blight disease severity in potato for all plantings (pooled data) at Kalyani	63
4.17	Equation for disease severity prediction of all planting (pooled data) for Kalyani location	64

4.18	Weather based prediction of crop age at first appearance of disease (CAFAD) for early planting by different models for Srinagar	65
4.19	Equation for prediction of crop age at first appearance of disease (CAFAD) for early planting for Srinagar location	65
4.20	Weather based prediction of crop age at first appearance of disease (CAFAD) for normal planting by different models for Srinagar	67
4.21	Equation for prediction of crop age at first appearance of disease (CAFAD) for normal planting for Srinagar location	67
4.22	Weather based prediction of crop age at first appearance of disease (CAFAD) for late planting by different models for Srinagar	68
4.23	Equation for prediction of crop age at first appearance of disease (CAFAD) under late planting for Srinagar location	68
4.24	Weather based prediction of crop age at first appearance of disease (CAFAD) for all plantings (pooled data) by different models for Srinagar	70
4.25	Equation for prediction of crop age at first appearance of disease (CAFAD) of all planting dates for Srinagar location	70
4.26	Weather based prediction of crop age at first appearance of disease (CAFAD) under early planting conditions by different models for Kalyani location	72
4.27	Equations for prediction of crop age at first appearance of disease (CAFAD) for early planting for Kalyani location	72
4.28	Weather based prediction of crop age at first appearance of disease (CAFAD) under normal planting conditions for Kalyani	73
4.29	Equation for prediction of crop age at first appearance of disease (CAFAD) for normal planting for Kalyani location	74
4.30	Weather-based prediction of crop age at first appearance of disease (CAFAD) for late planting by different models for Kalyani	75
4.31	Equation for prediction of crop age at first appearance of disease (CAFAD) for late planting for Kalyani location	75
4.32	Weather-based prediction of crop age at first appearance of disease (CAFAD) for all plantings (pooled together) by different models for Kalyani	77
4.33	Equation for prediction of crop age at first appearance of disease (CAFAD) of all plantings (pooled data) for Kalyani location	77
4.34	Weather based prediction of crop age at maximum disease severity (CAMDS) for early planting by different models for Srinagar	78
4.35	Equation for prediction of crop age at maximum disease severity (CAMDS) for early planting for Srinagar location	79
4.36	Weather based prediction of crop age at maximum disease severity (CAMDS) under normal planting by different models for Srinagar	80
4.37	Equation for prediction of crop age at maximum disease severity (CAMDS) for normal planting for Srinagar location	80
4.38	Weather based prediction of crop age at maximum disease severity (CAMDS) for late planting by different models for Srinagar	81

4.39	Equation for prediction of crop age at maximum disease severity (CAMDS) for late planting for Srinagar location	82
4.40	weather-based prediction of crop age at maximum disease severity (CAMDS) for all plantings (pooled data) by different models for Srinagar	83
4.41	Equation for prediction of crop age at maximum disease severity (CAMDS) for all plantings for Srinagar location	83
4.42	Weather based prediction of crop age at maximum disease severity (CAMDS) under early planting conditions by different models for Kalyani	85
4.43	Equation for prediction of crop age at maximum disease severity (CAMDS) for early planting for Kalyani location	85
4.44	Weather based prediction of crop age at maximum disease severity (CAMDS) for normal planting for Kalyani location	87
4.45	Equation for prediction of crop age at maximum disease severity (CAMDS) for normal planting for Kalyani location	87
4.46	Weather based prediction of crop age at maximum disease severity (CAMDS) for late planting at Kalyani	89
4.47	Equation for prediction of crop age at maximum disease severity (CAMDS) for late planting for Kalyani location	89
4.48	Weather-based prediction of crop age at maximum disease severity (CAMDS) for all plantings (pooled together) by different models for Kalyani	90
4.49	Equation for prediction of crop age at maximum disease severity (CAMDS) for all plantings (pooled data) for Kalyani location	91

LIST OF FIGURES

Figure No	Title	Page After
2.1	Symptoms of late blight of potato	8
2.2	Predicted global severity of late blight in potato production zones	9
2.3	Distribution of crop losses by late blight of potato in India	9
2.4	Disease triangle	14
2.5	Types of machine learning and their categories of algorithm	27
3.1	Methodology followed in objective 1	33
3.2	Methodology followed in objective 2	36
3.3	Two contrasting classes categorised by a hyperplane in SVM technique	37
4.1	Variations in weather parameters with year for different plantings (a) Early, (b) Normal and (c) Late, in Srinagar	92
4.2	Variations in weather parameters with year for different plantings (a) Early, (b) Normal and (c) Late, in Kalyani	93
4.3	Late blight disease parameters of potato for (a) Early (b) Normal and (c) Late planting conditions in Srinagar	94
4.4	Late blight disease parameters of potato for (a) Early (b) Normal and (c) Late planting conditions in Kalyani	95
4.5	Calibration of disease severity (DS) for Early Planting for Srinagar, *** = P<0.001	96
4.6	Calibration of disease severity (DS) for Normal Planting for Srinagar, *** = P<0.001	97
4.7	Calibration of disease severity (DS) for Late Planting for Srinagar, *** = P<0.001	98
4.8	Calibration of disease severity (DS) for All Planting (pooled data) for Srinagar, = P<0.001	99
4.9	Calibration of disease severity (DS) for Early Planting for Kalyani, *** = P<0.001, ** = P<0.01, * = P<0.05 and ns = non-significant	100
4.10	Calibration of disease severity (DS) for Normal Planting for Kalyani, ** = P<0.01, and ns = non-significant	101
4.11	Calibration of disease severity (DS) for Late Planting for Kalyani, *** = P<0.001, and ns = non-significant	102
4.12	Calibration of disease severity (DS) for All Planting for Kalyani, *** = P<0.001, ** = P<0.01 and ns = non-significant	103

4.13	Calibration of Crop Age at First Appearance of Disease (CAFAD) for Early Planting for Srinagar, DAP-Days After Planting, *** = P<0.001	104
4.14	Calibration of Crop Age at First Appearance of Disease (CAFAD) for Normal Planting for Srinagar, DAP-Days After Planting, *** = P<0.001	105
4.15	Calibration of Crop Age at First Appearance of Disease (CAFAD) for Late Planting for Srinagar, DAP-Days After Planting, *** = P<0.001	106
4.16	Calibration of Crop Age at First Appearance of Disease (CAFAD) for All Planting (pooled data) for Srinagar, DAP-Days After Planting, *** = P<0.001 and ns = non-significant	107
4.17	Calibration of Crop Age at First Appearance of Disease (CAFAD) for early planting at Kalyani, DAP-Days After Planting, *** = P<0.001, and ns = non-significant	108
4.18	Calibration of Crop Age at First Appearance of Disease (CAFAD) for Normal planting at Kalyani, DAP-Days After Planting, *** = P<0.001, ** = P<0.01	109
4.19	Calibration of Crop Age at First Appearance of Disease (CAFAD) for Late planting at Kalyani, DAP-Days After Planting, *** = P<0.001, ** = P<0.01	110
4.20	Calibration of Crop Age at First Appearance of Disease (CAFAD) for All planting at Kalyani, DAP-Days After Planting, *** = P<0.001	111
4.21	Calibration of Crop Age at Maximum Disease Severity (CAMDS) for Early planting at Srinagar, DAP-Days After Planting, *** = P<0.001	112
4.22	Calibration of Crop Age at Maximum Disease Severity (CAMDS) for Normal planting at Srinagar, DAP-Days After Planting, *** = P<0.001, * = P<0.05	113
4.23	Calibration of Crop Age at Maximum Disease Severity (CAMDS) for late planting at Srinagar, DAP-Days After Planting, *** = P<0.001	114
4.24	Calibration of Crop Age at Maximum Disease Severity (CAMDS) for All planting (pooled data) at Srinagar, DAP-Days After Planting, *** = P<0.001, * = P<0.05	115
4.25	Calibration of Crop Age at Maximum Disease Appearance (CAMDS) for early planting at Kalyani, DAP-Days After Planting, *** = P<0.001, ns = non-significant	116
4.26	Calibration of Crop Age at Maximum Disease Appearance (CAMDS) for normal planting at Kalyani, DAP-Days After Planting, *** = P<0.001	117

4.27	Calibration of Crop Age at Maximum Disease Appearance (CAMDS) for Late planting at Kalyani, DAP-Days After Planting, *** = P<0.001	118
4.28	Calibration of Crop Age at Maximum Disease Appearance (CAMDS) for all plantings at Kalyani, DAP-Days After Planting, *** = P<0.001	119

1. INTRODUCTION

There are enormous evidences from the past and present-day investigations stating that agricultural development is a prerequisite for overall growth and development of a nation (Bezemer and Headey, 2008). Agricultural contributions accounts for 13.7 percent of GDP and 57 percent of jobs in India. Agriculture provides the majority of raw materials to different sectors such as sugar, paper, textiles, handloom, food manufacturing, and dairy. Since the mid-1990s, India has increased its GDP per capita by more than 6% in a year, reduced poverty by half, dramatically reduced malnutrition, and turned itself into a global agriculture exporter. Many crops are grown in the Indian sub-continent, with rice and wheat being the most important food staples. Pulses, sugarcane, potatoes, oilseeds, and non-food products such as jute, tea, cotton, rubber, and coffee are also grown by Indian farmers (Malik and Kumar, 2021). Of all these crops grown in the country, potato has its own importance. Since it is a crop whose 85% parts of the plant is edible compared to other cereal crops where only 50% or even less part is edible. Also, potato is suited to regions where land is marginal and in our country majority of the farmers have marginal landholdings hence potato plays a crucial role in our Indian economy (Sharma *et al.*, 2018).

At present, potato ranks fourth in global production after wheat, corn and rice, with China being the leading producer of potato followed by India and Russia (Soare and Chiurciu, 2021). In India 74% of total production comes from Uttar Pradesh, West Bengal and Bihar i.e., concentrated near Indo-Gangetic planes (Rana and Anwer, 2018).

The history of potato crop is very captivating. Place of its origin and domestication is the Andean Region of South America, where it was indispensable for feeding the rising population. Potato has played a significant role in providing nutrition, in population growth, food security, and urbanization in many regions. In recent years, potato has turned out to be a leading crop in countries like China and India, and its area under production has increased over other food crops in Africa. The compliance of potato crop over several thousand years signifies the prime role of the potato as a climate-smart crop, predominantly grounded on its shorter vegetative period, water use efficiency, and production efficiency (Ortiz and Mares, 2017). The potato has realized global importance as a food item due to its incredible productivity in comparison to many other food crops. Dry matter production and protein content of potato is higher than cereals. The potatoes are a rich source of carbohydrates and energy but low in fats. Protein content is also low; however, it has got exceptional biological value of 90–100 (Camire *et al.*, 2009). Various compounds in potatoes have some antioxidant properties, have negligible fat content and low energy density comparable to legumes (Priestley, 2006). All these makes potato an important

food crop for the poor people from nutrition point. It has been recommended by FAO as a food security crop (Devaux *et al.*, 2014).

Being a crop of global importance, it is attacked by several insects and diseases causing significant losses in production and yield. Major fungal diseases of potato are late blight, early blight, black scurf, fusarial wilt/dry rot, wart, powdery scab, charcoal rot and major bacterial diseases are soft rot, common scab, bacterial wilt and brown rot, which cause considerable loss to potato production in field. Out of all the diseases late blight of potato is the most dreaded disease and it is caused by *Phytophthora infestans* (Mont) de Bary (Demissie, 2019). International Potato Centre (CIP) has estimated losses at global level in developing countries to be 15% (Sharma *et al.*, 2018). It is one among those diseases which possess the potential to cause 100% crop loss (Kobayashi *et al.*, 2012). It attacks leaves, stem and tubers of the plant (Agrios, 2005). Development of this disease is highly dependent on the prevailing weather conditions.

Weather denotes the instantaneous variations in the state of atmosphere (hours to days). It is often identified by the elements of weather namely temperature, atmospheric pressure, humidity, rainfall, wind velocity, cloudiness, sunshine hours etc. Climate is a long-term average of weather over a geographical region. (Patz *et al.*, 2000). Weather has a significant role in agricultural production. Temperature affects the rate of crop development right from sowing to harvest. Each species has an optimum range of temperature for its normal growth (Hatfield *et al.*, 2011). It is generally observed that vegetative growth increases with increase in temperature up to optimum, whereas reproductive growth is adversely affected due to reduction in viability of pollen grains and negative impact of higher temperature on fertilization and grain filling processes (Hatfield and Prueger, 2015). Precipitation is another important weather parameter which is an imperative element of hydrological cycle. All the water needs of plants are met by the water that falls through the process of precipitation on earth surface (Field and Heysfield, 2015). Relative humidity influences transpiration and water balance of the field thereby having an important role on plant growth (Ferrante and Mariani, 2018). Plants being photo-autotrophs requires ample supply of solar radiations throughout their lifespan (Kami *et al.*, 2010). Quality, quantity and duration of sunlight affects the process of photosynthesis as well as the yield of the plants. Higher or moderate wind velocity induces motion in plant canopy leading to crop lodging. (Py *et al.*, 2005). Direction and velocity of wind also influences spraying of fertilizers and pesticides, leading to spray drift (Gil *et al.*, 2015). Extreme events of weather elements, such as heat waves, frost, drought, floods etc have negative impact on plant growth and development (Niu *et al.*, 2014). In recent time, climate change has direct as well as indirect effects on plant pathogens, like increased change in pathogen population (Cogato *et al.*, 2019). Variations in pattern of rainfall or global rise in temperature might lead to shifting of crop growing season and might also affect the agriculture-based economies (Feleke, 2015). As

climate is varying and the impacts it can have on agricultural production are uncertain, hence for maximization of output and effective management of resources a precise weather forecast is necessary.

Disease forecasting is a management system, that can be used to predict the occurrence of change in severity of plant diseases (Shi *et al.*, 2009). These systems are used by producers to make economic decisions about disease control. With access to timely forecast, farmers would be in the position to decide the management practices which need to be employed in advance (Kumar, 2017). Forecasting enables the farmers to take need-based application of pesticides and fertilizers which reduces the cost of cultivation as well as minimises the use of chemicals thereby preventing soil, water and air pollution and various health hazards associated with the use of chemicals (Taylor *et al.*, 2003). Various diseases of crop plants have strong relationship with weather and environmental conditions which has the potential to cause significant economic losses. Thus, it is essential to integrate weather information with the forecasting models to strengthen the decision-making system (Fenu and Mallocci, 2020). For the prediction of outbreak of an infectious disease, forecasting is combined with decision-making processes. Further improvement in this integration can be made by the use of modelling and machine learning techniques (George *et al.*, 2019). Varied modelling approaches like artificial neural networks and multiple regression have been used in recent years for prediction of disease occurrence in crop plants.

Machine learning is defined as a budding branch of computational algorithms which are intended to outdo human intellect by learning from the neighbouring environment (Mahesh, 2020). Machine Learning depends on different algorithms for solving big data problems. It aims at teaching machines for efficiently handling the data. No clear borderline has been established between machine learning and statistical approaches. Some of the frequently used algorithms are- artificial neural networks, decision trees, support vector machines, naive Bayes, and *k*-means clustering (Bi *et al.*, 2019).

A disease forecasting model exploits information about weather (meteorological conditions), crop, pathogen(s) or different combinations of the three to forecast the out-break or fluctuations in severity of one or more diseases (Singh and Pundhir, 2013). Various models have been developed and used so far utilizing the regression or other statistical approach for prediction of yield, disease and pests etc for different crops in different regions of the country or world. Some of the widely used models are: TOM-CAST (Tomato Forecaster for early blight and anthracnose), FAST (Forecaster of *Alternaria solani* on Tomato); EPIBLAST, for blast of rice, BGRcast for bacterial grain rot of rice; JHULSACAST for late blight of potato; PLASMO for

downy mildew of grapes; NEGFY for late blight of potato (Charaya *et al.*, 2021) and Cashoo a fruit growth model for peach (Léchaudel *et al.*, 2005).

Nevertheless, the implementation of such models which have been developed so far is not universal (Singh and Pundhir, 2013). Despite significant attempts to forecast diseases in crop plants, many of these existing models frequently fail to provide accurate predictions to the farmers. The prevalence of weather and location influences the disease prediction and is one of the major issues, necessitating the use of more advanced procedures for unbiased evaluation of existing systems (Landschoot *et al.*, 2012). Keeping this background in view, attempts have been made to develop weather-based forewarning models for potato late blight (*Phytophthora infestans* (Mont.) de bary) incidence with the following objectives:

Objectives:

1. To establish relationship between weather variables and potato late blight incidence.
2. To develop and validate the weather-based forewarning model on incidence of late blight in potato.

2. Review of Literature

Over time, the ongoing global trade and the shifting climate have not only made the already advantageous environment worse for plants and animals but also have brought up new challenges that present agriculture must face (Fenu and Mallocci, 2021). In the global economy plant diseases cost over \$220 billion total losses each year. Insects and plant diseases alone are responsible for over 46% of all crop losses in India (Kumar *et al.*, 2021). Although India has already achieved significant progress in boosting the production area and productivity of important crops, in the past 15 years, agriculture has become less lucrative and more dangerous due to recurrent, uninterrupted outbreaks of pests in various parts of the nation. Around 15,000 crore rupees are currently spent annually in India's agricultural sector as a result of pests and diseases. Use of pesticides in the country on a yearly basis for agricultural production is to the tune of about 3150 crore Rupees (Chattopadhyay *et al.*, 2011). In general, farmers apply fungicides frequently and in larger quantities than recommended (Sharma & KC, 2004). This not only put farmers in financial crisis, but they also have detrimental effects on groundwater, the environment, and the natural enemies present (Chattopadhyay *et al.*, 2011). Producers, scientists, and agricultural extension specialists have also documented a deterioration in the efficacy of commonly used fungicides (Matson *et al.*, 2015).

2.1 Potato crop

Potato (*Solanum tuberosum* L.) is the most significant non-grain food crop in the world and a key component of global food security. It belongs to the *Solanaceae* family, which also contains tomato, brinjal, petunia, and tobacco. Its global significance, particularly in poorer countries, is quickly expanding, with production exceeding 359 million tonnes in 2020 (<http://www.fao.org>). Potato tubers are a primary source of starch, protein, antioxidants, and vitamins, and also act as a storage organ as well as means of vegetative propagation for the plant. Most of the potato cultivars are heterozygous, autotetraploid ($2n = 4x = 48$), shows inbreeding depression, and are sensitive to several damaging pests and diseases (Diambra, 2011).

2.2 Importance of potato crop

The majority of the world's undernourished individuals reside in poor nations; the FAO estimates that there are about one billion malnourished people worldwide (Barrett, 2010). For the most underprivileged and malnourished farming households in many of the nations, potatoes provide a major or additional source of food and nutrition. The importance of potatoes as a source of food, employment, and money, particularly in Asia, Africa, and Latin America, is evidenced by the consistently rising area and output of potatoes in emerging countries (Devaux *et al.*, 2020). Poor families cherish potatoes because they offer a source of dietary energy and

produce steady harvests in conditions where other crops frequently fail. It has been viewed as a crop for the future, that will provide food and nutritional security in poor countries (Scott *et al.*, 2019). Additionally, it works effectively in regions with a shortage of land but an abundance of labour, which is the case in the majority of the developing world. It produces significantly more nutrient-dense meals more quickly than any other field crop, on substantially less area, and in harsh environmental circumstances. Compared to around 50% of other grains, roughly 85% of the plant is edible for human consumptions (Lutaladio and Castaldi, 2009). Between 1960 and 2005, potato consumption in emerging nations climbed up to two or more times to 22 kg per capita year, and the potato's contribution to the food supply has been rising steadily.

We can conclude that potato is an important crop especially from food security point of view hence it was selected for the research work.

2.3 Important fungal diseases of potato

Potato is affected by various diseases that severely impair tuber yield, quality, and storage potential (Landschoot *et al.*, 2017). Potato is infected with several fungal, bacterial and viral diseases. Fungal diseases are a significant limiting factor in the potato production system and can result in financial losses both in the field and during transit and storage, among other biotic stresses (Tiwari *et al.*, 2021).

2.3.1 Late blight of potato: *Phytophthora infestans* (Mont.) de Bary is the organism responsible for late blight of potato. Depending on the local weather, this disease affects potato cultivation in India with production losses ranging from 5 to 90 percent. It causes damage to stem, leaves, and tubers. Losses would be greater if the disease manifests in an epiphytotic form in the early stages. If disease is not controlled in hilly locations, the drop in tuber production might be as high as 90% (Lal *et al.*, 2018).

2.3.2 Early blight of potato: Causal organism of the disease could be two species of genus *Alternaria* (*A. solani* and *A. alternata*), is the primary constraint in potato production at global level. It is causing damage in all the places where potatoes, tomatoes, peppers, and brinjal are grown. It can cause damage to leaves as well as tubers and can reduce yield upto 5-50% (Tsedaley, 2014).

2.3.3 Fusarium dry rot: *Fusarium sambucinum* and *Fusarium oxysporum* are the fungi responsible for *Fusarium* dry rot in potato. It affects the crop during storage condition. This leads to poor supply of potatoes to processing industries and human population (Tiwari *et al.*, 2021). Dry rot losses during storage might range from 25 to 60 percent. By destroying sprouting potato plants, fusarium dry rot of seed tubers can hinder crop establishment and cause up to

25% crop losses. More than 60% of tubers could get contaminated during storage (Wharton *et al.*, 2007). Around 88% of all post-harvest losses in the Chinese region of Gansu were reported to be caused by the dry rot disease (Du *et al.*, 2012).

2.3.4 Black scurf of potato: It is caused by *Rhizoctonia solani*. The fungus inhibits growth by making cankers on underground stems, and sprouts. It also disfigures tubers by producing black scurf (sclerotia) on their surfaces. In a short period of time, the fungus significantly reduces yield (up to 34 percent) (Kumar *et al.*, 2017)

2.3.5 Black dot of potato: It is a potato foliar disease and tuber deformity brought on by the fungus *Colletotrichum coccodes*. A decrease in potato quality is caused due to silvering of tuber skin that leads to the rejection of the produce in the market. After 18 weeks of storage, tubers with more than 60% infection lost about 10% of their fresh weight, whereas tubers with 0 to 1% infection lost only about 5% of their fresh weight

On comparing the losses in tuber yield caused by different fungal diseases of potato it can be concluded that late blight is the most severe of all potato diseases. Hence it is chosen for the present research work and studied in more detail.

2.4 Late blight of potato

The organism that causes potato late blight, one of the most serious potato diseases in the world and one that results in significant productivity losses, is *Phytophthora infestans* (Mont.) de Bary (Jones, 1998). The pathogen is extremely flexible and is capable of quickly adapting to different strains and fungicides. The first signs of late blight in a field are small, round, irregular in shape, water-soaked lesions that varies from light to a dark green in colour (Kirk *et al.*, 2013). Usually, these symptoms appear first in the lower leaves, where the environment is considerably more humid, (Martin *et al.*, 1994). However, if the weather is favourable and the disease has been introduced into the area by air flow, symptoms may also show up on the upper leaves (Martin *et al.*, 1994; Kirk *et al.*, 2013). In humid conditions, the lesions spread swiftly and result in brown, diseased areas with a hazy (indefinite) border. Along the margin of the lesions on underside of leaf, a 3-5 mm wide zone of white, downy mildew growth appears. The entire leaf eventually develop infection, die, and become lifeless (Agrios, 2005).

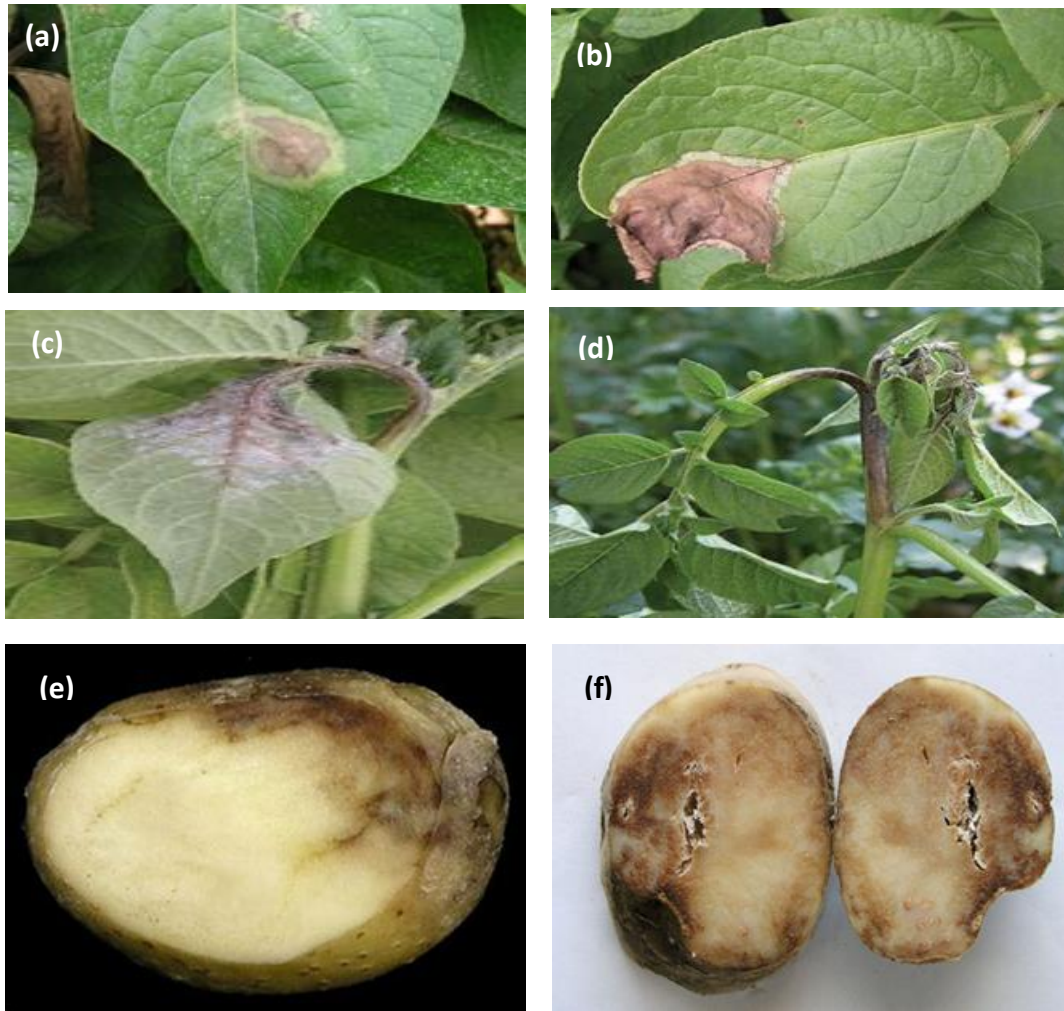


Fig. 2.1 Symptoms of late blight of potato: (a) initial symptom on leaves, (b) blighted leaf, (c) white cottony growth on downward side of leaf, (d) lesions on stem, (Source: [Late blight - Potato - Ontario CropIPM \(gov.on.ca\)](https://www.gov.on.ca/plants/pests/late_blight_potato/)) (e) brown discoloration on tubers, (f) symptoms on tubers (Source: <https://blogs.cornell.edu/livepath/gallery/potatoes/late-blight/>)

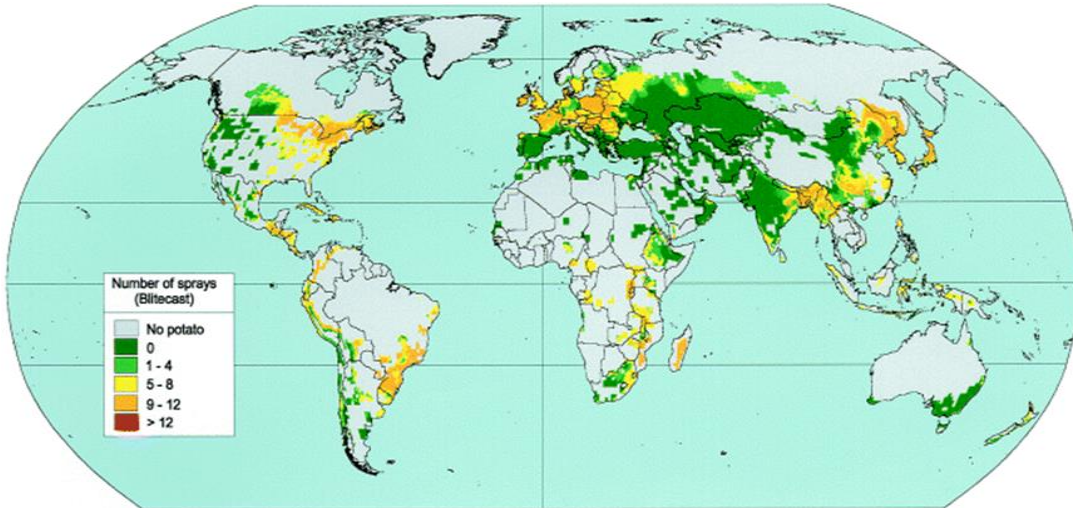


Fig. 2.2 Predicted global severity of late blight in potato production zones. It is expressed as the number of protectant fungicide sprays needed to control late blight. Predictions based on Blitecast, a late blight forecasting model, linked to global climate surfaces in a geographic information system (Hijmans *et al.*, 2000), (Source: <https://bsppjournals.onlinelibrary.wiley.com/doi/full/10.1046/j.1365-3059.2000.00511.x>)

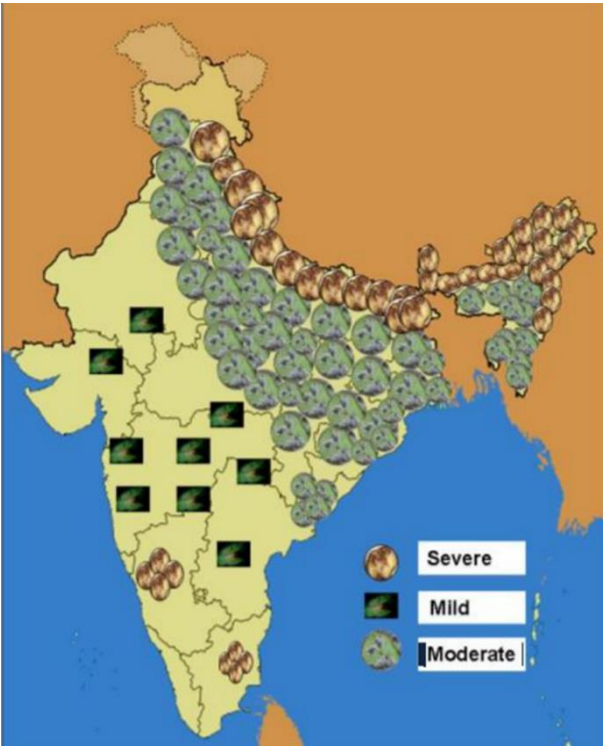


Fig 2.3 Distribution of crop losses by late blight of potato in India (Source: https://cpri.icar.gov.in/WriteReadData/LINKS/Manual_diseases_pest22be8b05-b856-4b56-8ef0-e8a172832540.pdf)

The deadliest of all potato diseases, late blight, which occurred in the middle of the nineteenth century, caused the Irish Famine. It affects both leaves in field condition and the tubers that are kept in storage, fully damaging a crop and causing a crop loss of 100%. (Tsedaley, 2014). Late blight is the most prevalent disease that affects tomatoes and potatoes worldwide. (Son *et al.*, 2008) The disease also poses a serious threat to tomato plants and other members of the Solanaceae family. Any time throughout the growing season, late blight can destroy the leaves and stems of potato and tomato plants. In order to reduce the primary inoculum, it is crucial to cover wastes with black plastic cover all through the season and keep seed tubers from infection (Cooke *et al.*, 2011). Early planting, sprouting of seeds well before planting, and the use of early-maturing varieties can all contribute in the management of late blight (Hermansen and Naerstad, 2009). The farms where crop rotations were practiced for three or more years between the potato crops showed the greatest reduction in early infection (Hannukkala *et al.*, 2007). The generation of resistant cultivars and the use of screening techniques have been crucial in the management of blight (Bhardwaj *et al.*, 2013). All these methods of management of late blight can be used effectively if we can forecast the disease well before the outbreak.

These losses can be kept to a minimum by using chemicals, cultural norms and host resistance. Although the most economically advantageous management strategy is to use host resistance, resistant cultivars are either not generated or, when available, are unable to withstand disease pressure on their own. This will require some additional support to be reinforced. In such case, chemical use is inevitable. Nonetheless, adopting chemicals is costly, there is a chance that pests will become resistant to chemicals, and also these chemicals are harmful to the environment. Hence application of pesticides depending on the need is essential for lowering chemical residues and management expenses.

2.5 Late blight progression in India

Between 1870 and 1880, the Nilgiri hills in India saw a late blight outbreak for the first time. During 1898–1900, it was reported in the Hooghly district of West Bengal, under subtropical plains, notably in the eastern half of India. In the northern region, it made its initial appearance in Darjeeling in 1883 and then quickly spread to other nearby hills. The disease was recorded in the Khasi Hills in 1885, the Kumaon Hills in 1887, and Shimla in 1902. It emerged in Assam and Bihar in a number of locations during the year 1913. In 1943, it was first documented in the plains of Uttar Pradesh. From 1958 till 1963, the epidemic struck Punjab every year with the exception of 1961. In fragments, the disease was detected in Rajasthan in 1958 and in Gujrat in 1968. Following this, late blight outbreaks are a common occurrence, with increased disease severity in hills and moderate to severe levels in plains (Lal *et al.*, 2018). From this we can conclude that wide range of climates, from subtropical to temperate Himalayan conditions, are

suitable to cultivate potatoes (Bajracharya & Sapkota, 2017). Hence, we can conclude that late blight is an important disease of potato crop in the world and in India as well.

2.6 Weather and disease development

Both plants and diseases need a specific minimum temperature to flourish. The sequence of steps in disease cycles, including pathogen survival, dissemination, penetration, development, and reproduction rate, are all influenced by temperature. In general, excessive moisture and heat, encourage the onset of disease as well as the germination and growth of fungal spores from a variety of infections (Agrios, 2005). Moisture makes it possible for pathogen to cause disease, and dry spells destroy the pathogen (Prank *et al.*, 2019). Increased levels of atmospheric water vapour promote the development of healthier, larger canopies in the crops, which result in conditions that are favourable for pathogens by retaining moisture as well as leaf wetness and RH for extended periods of time (Coakley *et al.*, 1999). Increased CO₂ levels affect the host and the pathogen in different ways. Increased CO₂ levels leads to increase in leaf area, leaf thickness, number of leaves, total leaf area/plant, and diameter of stems and branches (Bowes, 1993). The prevalence of rust, powdery mildew, Alternaria blight, Stemphylium blight, and Anthracnose diseases are all favoured by the dense crop canopy.

2.7 Effect of weather on late blight of potato

Different environmental factors affect the growth of pathogens. The ambient temperature has an impact on the host plant's growth and development. Fungal infection is more prevalent under relatively higher humidity and optimum temperature. In general, plant development is influenced by the type of soil, climate, wind, nutrition, and solar radiation. Environmental variables also affect the spread of disease. The growth of disease-causing organisms is favoured by wet foliage (Gokulnath and Usha Devi, 2017). Environmental factors have a significant impact on disease epidemiology (Hardwick, 2006). For spore development to proceed, the environment must be moist for at least 7 to 10 hours (Martin *et al.*, 1994). Spores are more noticeable during wet nights or bouts of rain. Animals, wind, splashing rain, all spread sporangia to healthy plants in adjacent fields (Martin *et al.*, 1994; Kirk 2009; Kirk *et al.*, 2013). Low temperatures (4–12°C) are required for sporangia germination from zoospores whereas for direct sporangia germination, high temperature (20–27°C) is required. Sporangia and zoospores can only grow in free water. High light intensities destroy the spores, while low light intensities (300–390 nm) encourage sporangial germination. For the infestation and growth of late blight, night temperature of 10–16°C, followed by light rain, fog, or heavy dew, and high relative humidity are ideal (Kirk, 2009; Kirk *et al.*, 2013). The growth of organisms in the field is delayed or stopped by temperature above 30 °C, but this does not kill the pathogen. The

fungus can restart its sporulation once the temperature is favourable, but only if the relative humidity is high enough (about 100 %) (Agrios, 2005).

Wind and rain carry the spores to healthier plants, where the disease cycle starts again. During the various stages of its life cycle, the humidity and temperature that prevail have a significant impact on the development of late blight outbreaks. The fungus can go through multiple reproductive cycles in a season, which explains why disease spreads so rapidly once the pathogen establishes itself in a field. When the weather is consistently moist, all of the aboveground parts of the plant that are fragile succumb to blight and rot, releasing a distinct odour. In a matter of days or weeks, entire potato plant as well as other plants in the entire field can become blighted and die. The pathogen's activities get reduced or terminated in dry weather. Existing lesions stop growing, turn black, curl, and wither, and there appears no oomycete on the underside of the leaves. When the weather gets moist again, the oomycete starts its activities, and the disease progresses swiftly once more (Agrios, 2005).

From all above-mentioned literature we have realised the importance of weather in the development of late blight disease. Hence, for management of disease in-season weather data has significant importance.

2.8 Acquisition of weather data

Meteorological data are required for weather forecasting and forewarnings, for localized weather-dependent activities and for the purpose of research in meteorology, climatology, hydrology etc. Additionally, accurate location-specific data are necessary for parameterization and calibrating models. The credibility of the model estimates and subsequent DSS outputs are therefore dependent on the data source. (Rivington *et al*, 2006). Weather data can be obtained from different sources and a few of these sources are mentioned here.

2.8.1 Automatic weather station (AWS): It is a system which records and conducts its observations automatically through multiple integrated sensors. A weather station has a system of integrated components of a weather station that automatically measure, record, and sometimes transmit weather data. It is similar to traditional weather station but all measurements are automated, thus it can be single-site or function as a weather network. Datasets from AWSs and MODIS TERRA satellite were utilised to assess threats of forest fire in Madhya Pradesh, India by Babu *et al*. (2017). Using a network of automated weather stations, a real-time system was developed to monitor drought in Spain (Vicente-Serrano *et al*., 2022). In Amsterdam with the help of AWSs prospect of rainfall in urban areas was monitored (De Vos *et al*., 2017).

2.8.2 Weather satellite data:

A type of Earth observation satellite is called a weather satellite, sometimes known as a meteorological satellite. It is used chiefly to track Earth's weather and climate. On April 1st, 1960, the first weather satellite was launched. Over the past 25 years globally the weather satellites have enhanced weather analysis and forecasts (Smith *et al.*, 1986).

2.8.3 Weather radar:

It is a device that delivers electromagnetic energy pulses into the sky to locate precipitation, gauge its velocity and intensity, and identify the type of precipitation—such as rain, snow, or hail. Doppler weather radar is used to analyse quantitative forecast of depressions during the Indian monsoon season (Routray *et al.*, 2010). Indian Doppler Weather Radar is used for Locust Swarm Detection and Tracking (Amarjyothi *et al.*, 2021).

2.8.4 SoDA MERRA-2 data

The Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) is a web service which provides data of Temperature, Relative Humidity, Pressure, Wind speed and direction, Rainfall, Snowfall and Snow depth. Weather data are obtainable from January 1980 onwards. MERRA-2 Data was used to Model Net Radiative Measurement of Meteorological Parameters in a Sub-Saharan African Town (Aweda *et al.*, 2021). Oceanic heat content and satellite-era cyclones were analysed during 1980–2014 over Bay of Bengal using MERRA-2 data (TS *et al.*, 2018).

Weather data can be acquired from various sources depending on the availability of data for that particular location and requirement of the study.

2.9 Disease forecasting

A descriptive definition of disease forecasting offered by Miller and O' Brien (1952) is still relevant today. It says, “Forecasting involves all the activities in ascertaining and notifying the growers of community that conditions are sufficiently favourable for certain diseases, that application of control measures will result in economic gain, or on the other hand, and just as important that the amount expected is unlikely to be enough to justify the expenditure of time, energy and money for control”. The assumptions on how the pathogen interacts with host and environment, serves as the foundation for forecasting systems (Fig. 1). This interaction is called as disease triangle (Mahapatra *et al.*, 2018).

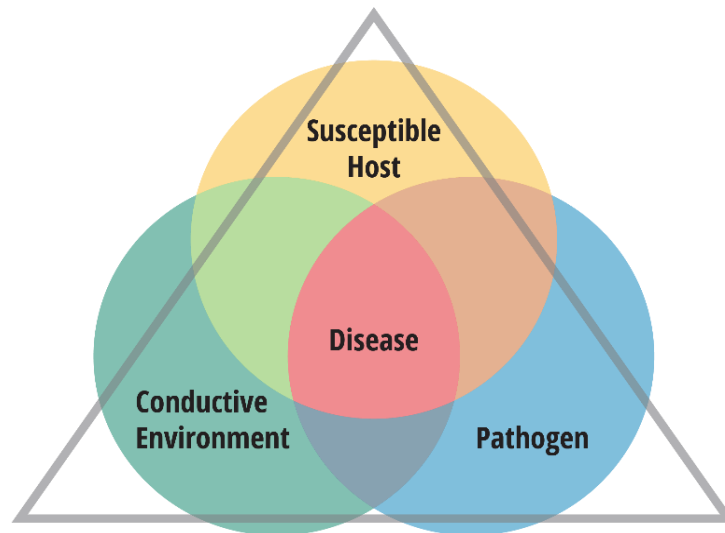


Fig.2.4 Disease triangle (Source: [Sustainable Plant Disease Protection Strategies to Keep Your Customer's Crops Healthy \(precisionfarmingdealer.com\)](https://precisionfarmingdealer.com))

A theoretical model called the disease triangle depicts the relationships between the host, the environment, and the pathogen (Scholthof, 2007). The triangle is complete when the host is vulnerable, the pathogen is virulent, and the environment is conducive to the formation of infection, (Munir, 2018). A disease forecasting system is built to predict when the environment would be favourable for disease development. Disease forecasting is a component of applied epidemiology, consequently, effective forecasting requires an understanding of epidemiology (the progression of disease under the impact of aspects related to the host and pathogen) (Mahapatra *et al.*, 2018). Forecasting is an analytical tool beneficial during epidemics that can guide in the judgment about policy and epidemic management in response to the course of real-time outbreak (George *et al.*, 2019). Management choices could be influenced by prediction model based on the correlation between environmental variables like weather parameters at the time of management and the severity during the late-season diseases (Taylor *et al.*, 2003). The models that emerge make it possible to investigate the variables including weather parameters that influence disease epidemics and to devise control strategies to reduce yield losses (Kaundal *et al.*, 2006).

In order to predict the occurrence of the plant disease in a specified area and time, disease forecasting is essential, so that proper control measures could be undertaken in advance and crop losses could be reduced. Through disease forecasts we can predict probable outbreaks or increase in intensity of any particular disease in a particular location. In general, it requires well organized team work, time, energy and finance. This can be an aid to the timely management of diseases. Disease forecasting model is specific to a particular disease, crop, climate & region.

The development of forecasting models depends on assumptions, decision rules and basic data. Models could be developed for a specific climatic condition for a specific disease, it might have certain assumptions about site specific conditions. Hence might not apply for all variables like timing of model initiation, host phenology, and host range, amount of initial inoculums, weather condition between the cropping seasons. With the increase in computing power and the amount of data available, disease forecasting systems might become more useful in future. Good forecasting systems is very much essential in the context of climate change as plant disease forecasting systems can give information to help grower's management decisions either to avoid initial inoculums or to slow down the rate of an epidemic during the season. These two concepts are important because they often differentiate the risk for a monocyclic disease versus polycyclic disease, where there are multiple infection cycles, and a forecasting system can be used to time appropriate management tactics, such as a foliar fungicide application. It should be noted that some plant disease forecasts focus both on avoiding initial inoculums and also on reducing the rate of the epidemic during the season. In these contexts, plant disease forecasting systems emphasize the timely adaptation of plant protection measures to protect the crop before the onset of the disease, so that the crop could be grown healthy.

2.10 Previous work on disease prediction and forecasting

For the first time a late blight forecasting technique was created by Van Everdingen (1926), known as "Dutch rules" for Holland, using environmental variables such as temperature, relative humidity, rainfall, and dew etc. Control measures were implemented using the following criteria: (i) an overnight period with at least four hours of dew; (ii) minimum temperature of 10°C; (iii) the following day should have a minimum of 0.8 mean cloudiness; (iv) at least 0.1 mm rainfall within the next 24 hours. (Van Everdingen, 1926). Since the late 1970s, escalating globalisation has caused pathogen genotypes to migrate across the globe, dislodging dominant, older clonal lineages or genotypes (Goodwin *et al.*, 1994). As a result of which new lineages have emerged and spread, some of which shown enhanced aggression (Mizubuti and Fry, 1998). Based on R gene stacks, it seems likely that growing genetic diversity of *P. infestans* is decreasing the longevity of late blight resistance (Li *et al.*, 2012). Changing climate, population diversity, and other factors have made Potato late blight control more challenging (Baker *et al.*, 2005). Currently, exhaustive fungicidal sprays are commonly done because of the greater risk of potato late blight epidemics in input intensive agriculture, which is linked to increased pathogen aggressiveness This corresponds to more than 10 sprays every season in western Europe, whereas crops in certain other nations may even get up to 20 applications of fungicide (Dowley *et al.*, 2008). Among the few IPM strategies for management of late blight that has long been accepted there is a need to build late blight forecasting models to be used as decision support systems (Fry, 2012).

Since then, a large number of forecasting techniques based on minimum temperature, relative humidity, disease severity and other parameters have been devised throughout the globe Bhattacharyya *et al.*, (1982), but the matter of concern was that majority of them were region-specific. BLITECAST, PhytoPRE, PHYTEB, ProPhy, and NEGFRY etc. were the models that have been developed globally. Recognizing the temporal and spatial characteristics of plant disease outbreak is the foundation for development of mathematical and statistical models to manage various diseases of plants, decision-making tools were developed for preventative action and timely fungicide applications (Campbell and Madden, 1990).

Singh *et al.*, (2000) developed forecasting algorithms for Indian contexts using some of these ideas. Singh *et al.*, (2019) used disease cycle and climatic conditions and experimental data collected in Himalayan region for two consecutive crop seasons (2017 & 2018) for development of forecasting models and decision support systems using stepwise regression. Despite advancements in the field of late blight forecasting, a worldwide disease forecasting system without local calibration is still required (Singh and Sharma, 2013). A multi-model platform – SISALERT was developed by Fernandes *et al.*, (2011) with the help of advanced disease risk analysis models, to harness hourly weather station data for forecasting information. A General-purpose and flexible simulation models were employed for forecasting the onset of diseases based on meteorological data. Using the simulation models, a system for acquiring meteorological data in close to real-time along with local weather forecasts, a disease warning system was developed. Sannakki *et al.*, (2013) conducted research in which weather was predicted using a modified k-Nearest Neighbour (NN) method and Feed Forward Neural Network, and with the help of variables like humidity and temperature the disease infection was predicted in grape.

The effectiveness for detecting wheat leaf rust at the canopy scale and at three distinct leaf area index (LAI) levels—high, medium, and low were examined by Azadbakth *et al.*, (2019). Four techniques—Gaussian process regression, random forest regression, v-support vector regression, and boosted regression tree—were utilised to analyse the effectiveness of rust detection. Disease intensity was also predicted using the hyperspectral reflectance data collected under various environmental conditions. Saha *et al.*, (2020) examined three years' aerobiological data, including the concentration of pathogenic spores (*Ustilaginoidea virens*) over the rice canopy in west Bengal state. Additionally, the stages of crop growth throughout the *rabi* (winter or dry) and *kharif* (rainy) seasons when false smut disease develops quickly were considered. By calculating the spore concentration above the rice canopy in West Bengal, the regression model created helped farmers to predict the onset of false smut disease in rice in advance. Disease prediction is novel techniques. Several works were done in

prediction of diseases utilizing various techniques for different crops and different diseases. Different techniques performed differently in prediction of disease.

2.11 Importance of disease Forecasting

Forecasting of disease is necessary for three important reasons: the first is financial, the second is protection, and the third is ethical use. The economic issue is one of lowering production costs through timely application of control methods, most commonly fungicides. This reduces fungicide waste by using these only when they're needed, which is usually at the beginnings of an epidemic. Protection includes not only of the crop – decreasing pesticide phytotoxicity – but also of the environment – limiting exposure to non-target species, workers, and final consumers. Pesticide loading has been reduced by 50% in some countries, particularly in Scandinavia (Jorgenson *et al.*, 1996). Forecasting can help to predict when a condition will become 'critical,' and hence have a financial impact. With some diseases, it's critical to be able to predict the disease's first appearance, because future control would be difficult owing to the lack of, say, effective chemicals to eradicate the disease after it has been established. For other diseases, a certain degree of infection may be tolerated, especially on portions of the plant that contribute little loss to yield or quality, therefore forecasting is all about anticipating when the disease will damage the plant's vital parts or critical stages of its growth. Thus, disease forecasting and early identification are crucial for farmers to effectively implement preventative measures (Martinelli *et al.* 2015). All the studies show the importance of forecasting in management of disease. Although various models are developed for disease forewarning but every model has its own limitations. hence, there is a great scope for improvement in the field of forecasting.

2.12 Machine learning Technique to forecast disease

Machine learning is concerned about development and investigation of frameworks that can gain from informational datasets, enabling system to learn without being explicitly programmed. The use of machine learning (ML) techniques in agriculture includes agricultural crop management, yield estimation (Chlingaryan *et al.*, 2018), disease detection (Khalili *et al.*, 2020), and detection of weeds and quality of different crops (Liakos *et al.*, 2018; Wang *et al.*, 2019).

Khalili *et al.*, (2020) developed an explicit model for detection of charcoal rot in soybean by carefully examining the symptoms in various parts of the plants. 2,000 soybean plants in their natural environment were included in the database. Multilayer Perceptron (MLP), Regularized Logistic Regression (LR-L1 and LR-L2), Random Forest (RF), Gradient Tree Boosting (GBT) and Support Vector Machines (SVM) supervised ML classifiers were trained to distinguish

between infected and non - infected plants. Through the study of the specified feature set, the GBT classifier outperformed these models with a success rate of 96.79 percent.

Ahmed *et al.*, (2022) proposed a model of artificial intelligence (AI) based on the k-NN classifier and the k-efficient clustering method with a purpose to evaluate k-NN before and after clustering in the prediction of soybean disease in order to choose the most effective method for plant disease forecasting. Other purpose was to evaluate the performance of k-mean, k-medoids, and k-efficient. Results showed that k-NN with a high k-efficient was more effective than other models in terms of accuracy, precision, F- measure and running time. Machine learning is an emerging technique for timely and accurate prediction of the disease and a lot more work needs to be done in this field to tap its potential.

2.13 Decision Support System

Decision Support System (DSS) is an actively interacting software that assists decision-makers in assembling pertinent data from a variety of sources, including raw data, documents and previous insights. The database, model, and user interface make up the framework of DSS (Rinaldi and He, 2014). In many nations, including the United States, Australia, Norway, Denmark, Spain, the United Kingdom, Germany, the Netherlands, Italy, France, Sweden, and Israel, DSSs have been devised to manage and diagnose different plant diseases since 1990s (Bouma, 2007; Fabre *et al.*, 2007). These technologies were created to combat diseases that spread aggressively or need to be consistently regulated (e.g., late blight of potato, apple scab, downy mildew of grapes etc.) (Shtienberg, 2013).

Plant pathogens are effectively suppressed by combining a number of management strategies, each of which may have a different efficiency, durability and costs. The managers must choose from a variety of options while determining whether or not to use a pesticide. Arriving at a reasonable conclusion for the management of the disease is challenging because the predominance of pathogens and the severity of the diseases they cause differ significantly with location and time. As a result, reasonable and profitable management needs to take into account a numerous factor (Shtienberg, 2013). Some of the systems developed for late blight are given below:

Small *et al.* (2015) developed a DSS for management of late blight in potato and tomato named as BlightPro, a system that integrates a number of models and allows for the prediction of disease dynamics based on environmental factors, crop data, and management strategies. The system automatically acquires weather data from a nearby weather station, as well as region specific forecast weather data from the National Weather Service's National Digital Forecast Database, after growers specify the coordinates of their field in USA.

Gu *et al.* (2016) developed a forecasting model called BLITE-SVR for late blight of potato in Korea, which is used for prediction of first date of appearance of disease using data from 1976 to 1985 and from 2009 to 2012. The statistical method employed is support-vector regression (SVR). They gathered 13 different types of weather data, such as temperature, humidity, evaporation, solar radiation, wind velocity etc., for their prediction model. These data showed a very strong relation to the first date of appearance of disease.

Kleinhenz and Jörg (1999) developed a DSS SYMPHYT in Germany, in which there are two modules SIMPHYT I and SIMPHYT II. The date of *Phytophthora infestans*' initial appearance is predicted by SIMPHYT I which require daily rainfall as well as 3-hourly averages of temperature and relative humidity as inputs. SIMPHYT II suggests a spraying strategy and keeps track of when *Phytophthora* epidemics start. In response to request from extension service a new model SIMPHYT III has been developed providing information on *P. infestans* infection pressure and dry periods. Results from SIMPHYT III are frequently used in the warning systems. The most crucial tool for comprehensive potato crop protection is SIMPHYT I/II, which has been widely used in crop protection operations within Germany.

Borovski (2021) created the VNIIFBlight DSS with the goal of reducing potato crop losses brought by late blight. It has two variants. The first variant of the VNIIFBlight DSS assesses weather conditions as favourable or unfavourable for the late blight infections on potatoes. The new version of VNIIFBLIGHT DSS was created to prevent the spread of both early and late blight of potato. The new version of this DSS enables a user to accomplish two roles, in contrast to the earlier VNIIFBlight version, which can only determine whether the current weather conditions are favourable or unfavourable for the late blight- Selection of the best fungicides and Determination of the most suitable dates for administration of fungicides.

Thus, decision support system plays crucial role in reducing the time taken and improving the efficiency of disease prediction.

2.14 Different algorithms used in plant disease prediction

2.14.1 Support Vector Machine (SVM) in disease prediction

Morgan *et al.* (2021) conducted research to test the ability of six current classification methods (artificial neural network, naive bayes, support vector machine, decision tree, and random forest) to categorise and forecast diseases in soybean and mushroom. Their study's major goal is to provide classification techniques for disease categorization and forecasting in datasets that comprise of raw measurements rather than pictures. All the six algorithms performed well on

the mushroom dataset, while the artificial neural network and k-nearest neighbor algorithms performed best on the soybean dataset

Bhatia *et al.* (2020) forecasted powdery mildew illness in tomato plants, this work proposed to create a hybrid Support Vector Machine (SVM) and Logistic Regression (LR) algorithm. Before data was supplied to an LR classifier, SVM was used to reduce data noise. The SVM classifier used the Adaptive Sampling based Noise Reduction (ANR) approach to reduce noise. Accuracy, f1-score, and Area Under Curve were used to compare the performance of the generated models. The suggested method has been successfully applied to the dataset and outperformed the SVM and LR classifiers in terms of accuracy, AUC, and f1-score metrics in predicting powdery mildew.

Kaundal *et al.* (2006) conducted a study to evaluate the utility of SVM models in comparison to the current artificial neural network and traditional multiple regression models in order to forecast the intensity of the rice blast based on the local weather conditions both within and among different locations or years, Cross-location models within each year were designed and independently validated using REG, BPNN, GRNN, and SVM methods. The case study showed that SVM outperforms traditional REG methodologies and contemporary machine learning techniques in predicting plant diseases.

Huang *et al.* (2022) presented a forecasting model for the *Alternaria* Leaf Spot (ALS) disease in apples based on spatial-temporal meteorological data. To efficiently gather information for disease surveys, a mobile internet-based questionnaire was developed. Then temperature and humidity data were subjected to a sensitivity analysis in order to discover disease-sensitive meteorological parameters that could be used as model inputs. Four machine learning algorithms, including logistic regression (LR), Fisher linear discriminant analysis (FLDA), support vector machine (SVM), and K-Nearest Neighbors (KNN), were used to create the disease forecasting model for *Alternaria* leaf spot of apple. The KNN algorithm, which generated an overall accuracy of 88 percent and a Kappa of 0.53 in this investigation, was recommended. SVM is used by a large number of researchers for the prediction of disease in various crops. In some it has performed well whereas in others SVM was outperformed by other techniques such as KNN, ANN etc.

2.14.2 SMLR in disease prediction

Naqvi *et al.* (2016) developed a model for bacterial leaf blight of rice based on in season dataset available for intensity of disease and climatic variables. Three rice cultivars (Basmati Super, IRRI-24, and TN-1) that are particularly sensitive to the disease were examined in this study. Weather data on daily maximum and minimum air temperatures, morning and evening relative

humidity, rainfall, wind speed, and daily sunshine hours were considered. In order to identify potentially helpful parameters and to eliminate ineffective parameters, stepwise regression analysis was carried out. Step-wise regression analyses indicated that the morning relative humidity and wind speed were the most important environmental factors influencing the disease development.

Narayana *et al.* (2006) carried out field trials during kharif and rabi season to examine the development of groundnut rust (*Puccinia arachidis*) in accordance to weather elements. They created an environment-based linear prediction model that would use stepwise multiple regression analysis to forecast rust before it really appeared. It was observed that variables with the highest link to the rust disease during the kharif season were maximum temperature, minimum temperature, maximum relative humidity, wind speed, sunshine hours, rainfall, and crop age however, during the rabi season, crop age, relative humidity, wind speed, rainfall, evaporation, and maximum and minimum temperatures all had a strong correlation with the development of rust on groundnuts.

Ehetisham-ul-Haq *et al.* (2017) devised a model to forecast the effect of *Dysdercus cingulatus* vector and environmental factors on boll rot of cotton. Weather variables analysed using SMLR were maximum and minimum air temperature, relative humidity and rainfall to reduce the damage caused by disease and overcall cost of management.

Binyamin *et al.*, (2022) conducted a study to predict the yellow mosaic virus disease in mungbean. Correlation and stepwise regression analysis were used to gather and analyse week wise and day wise data on disease incidence and environmental factors. For the majority of the mungbean genotypes, it was observed that actual MYMV disease incidence levels, and that predicted by the model were extremely close. SMLR is utilised by a large number of researchers for the prediction of disease in various crops. In some it has performed well whereas in others SMLR was outperformed by other techniques.

2.14.3 Linear and non-linear regression models in disease prediction

In regression dependence studies, it seeks to represent observable data in the most straightforward, practical, and elegant manner feasible (Weisberg, 2005). Regression models are regarded as empirical models.

Simple linear regression model: It is a model with a single regressor, x, and a straight-line relationship between y, the response, and x. A SLR model is represented as:

$$y = \beta_0 + \beta_1 x + \varepsilon$$

Where, β_0 and β_1 are unknown constants and x is an independent variable and y is dependent variable (Montgomery *et al.*, 2021).

Multiple linear regression model: This model includes multiple regressor variables. A MLR model with two regressors is represented as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$$

where β_0 , β_1 , and β_2 are unknown constants and x_1 and x_2 are independent variables and y is dependent variable (Montgomery *et al.*, 2021).

Non-linear regression models: These models are centred on the nonlinear dependence of the prediction equation on one and maybe with more unknown inputs. This association between the predictor and responder adopts a specific functional pattern (Smyth, 2002). nonlinear regression model has the form

$$Y_i = f(x_i, \theta) + \varepsilon_i$$

where $i=1,2,3,\dots,n$, y_i is the response and f is the function of covariate x_i and parameter vector θ and ε_i are random errors.

2.15 Models developed for forecasting of late blight disease

Epidemics of plant diseases are anticipated using a variety of statistical techniques. A model that takes into consideration a variety of evolving environmental conditions is required for better forecasting of disease. A variety of economically significant crop diseases are correlated with weather conditions during the growing season. Forecasting crop diseases is essential for boosting crop production. In many regions of the globe, late blight outbreaks have increased in frequency, therefore forecasting is necessary. Several mathematical models were created to handle this problem from the 1990s to the 2020s (Table 2.1)

Van Everdingen (1926) was a forerunner in employing "Dutch Rules" to predict the advent of the late blight in Holland. These rules are based on four weather variables: dew periods, night temperatures, cloudiness, and rainfall. Even though these guidelines weren't implemented globally, they did provide certain workers some drive. After that, Beaumont Rules was introduced, which advocated minimum temperature of 10°C or higher and at least 75% relative humidity for two consecutive days as required conditions for the disease (Beaumont, 1947). In the UK, all these anticipated late blights just. Various models developed for forecasting late blight of potato and their specifications are given in the table below:

Table 2.1: Models developed for forecasting late blight of potato and their specifications

Reference	Model's name	Variables used	Implementat ion location	Limitations
Cook, 1949		Daily average temperature and rainfall.	Virginia, Connecticut and British Columbia,	It was not found to be effective in England, Wales, Iowa, Wisconsin and Indiana

Bourke (1953)		Hourly temperature, relative humidity and rainfall	Ireland	Since this model has been developed for the temperate conditions of Ireland and it may not be suited for use in other locations
Hyre (1954)		Daily rainfall, maximum and minimum temperature	North Eastern, USA	
Smith (1956)		Minimum temperature and hourly relative humidity		The Smith criteria was developed for the temperate climatic conditions of England and Wales and may not be directly usable in other location
Wallin, (1962)		Hourly relative humidity and temperature	North Eastern, USA	
Ullrich and Schrodter (1966)		Hourly temperature, relative humidity, and rainfall	Germany	The model assumes the same amount of initial inoculum is present every year, which may not be justified all times
Krause <i>et al.</i> , (1975)	BLITECAST	Daily rainfall, maximum and minimum temperature	Ohio, USA and Mexico	
Fry <i>et al.</i> , (1983)	Modified BLITECAST	Daily rainfall (mm), hourly average temperature and relative humidity	California, USA	This model was developed to be used with chlorothalonil. It was not developed to predict timing of the first fungicide application
Forsund (1983)		Daily maximum and minimum air temperature (C), relative humidity at	Norway	This model does not differentiate between initial infection conditions and subsequent infection

		noon, and daily rainfall (mm)		events in late blight; it provides a warning of the risk of infection anytime during the season
Gutsche (1993)	PROGEB	Hourly temperature, relative humidity and rainfall	Germany	Integrates forecasting models for the major pests of potatoes and cereals
Forrer (1993)	PhytoPRE	Hourly temperature, relative humidity and rainfall	Switzerland	This model was developed based on observed disease progress curves in Switzerland and would need to be modified for use in other places
Schepers, (1995)		Temperature, relative humidity, rainfall and leaf wetness	Netherlands	This model was developed for weather conditions in the Netherlands and is based on the use of cymoxanil fungicides, which are not registered for use in other locations
Hansen (1995)	NEGFRY	Hourly temperature, relative humidity, and rainfall	Europe	NEGFRY is a personal computer-based model developed in Denmark. It uses the "negative prognosis" model of Ullrich and Schrodter (1966) to forecast risk of late blight outbreak on potato, and the model of Fry et al. (1983) to time subsequent fungicide applications during the season.
Johnson <i>et al.</i> , 1996		Daily total rainfall, daily minimum temperature		This model has not been tested
Singh <i>et al.</i> , (2000)	JHULSACAST	Temperature and relative humidity	India	It is a region-specific model and requires hourly data.

Singh <i>et al.</i> , (2016)	INDO-BLIGHTCAST	Temperature and relative humidity	India	Accuracy is only 75% and it considers only temperature and RH
Gu <i>et al.</i> , (2016)	BLITE-SVR	13 kinds of weather data, including temperature, humidity, evaporation		There are limitations in explaining the effects that variables have on other variables

Some of the important late blight forecasting models are discussed in brief here

2.15.1 SIMBLIGHT1

In years with high soil moisture, the nearly 20-year-old SIMPHYT1 model was unable to forecast the initial appearance of potato late blight. Therefore, SIMBLIGHT1 was generated. As input variables, it requires data on temperature, relative humidity, soil moisture, crop prevalence, and cultivar vulnerability. SIMBLIGHT1 generate a cumulative risk score for multiple groups of emergence dates when a particular threshold was reached and signalled the onset of the epidemic (Kleinhenz *et al.*, 2007).

2.15.2 BLITE-SVR

The BLITE-SVR late blight prediction model was created using late blight disease data from 1976 to 1985 and 2009 to 2012, and was used to predict and confirm the initial date of incidence. SVR was a statistical technique with acceptable performance. The earliest date of late blight appearance was strongly correlated with 13 different types of weather variables, including temperature, humidity, evaporation, and other variables (Gu *et al.*, 2016).

2.15.3 JHULSACAST

"JHULSACAST" model was created to forecast the appearance of late blight in western Uttar Pradesh. weather data from Punjab were analysed during a 15-year period (1997–2012). The onset of Late Blight and weather patterns were linked using artificial neural network, a machine learning technology. The meteorological variables studied included maximum temperature, minimum temperature, maximum humidity, minimum humidity and rainfall. A forecast accuracy of 90.9% was able to achieve. (Sharma *et al.*, 2018).

2.15.4 INDO-BLIGHTCAST

"INDO-BLIGHTCAST", a model for predicting late blight, was created by the Central Potato Research Institute in Shimla, India, using meteorological information and late blight emergence

dates from four locations in the Indo-Gangetic plains. The created model was tested against independent data sets at three sites in the plains, two in the plateau region, and three in the hills. The model estimates the physiological days (P-days) and night time mean relative humidity over a period of seven days (RH). Late blight was predicted to appear within 15 days if the cumulative effective temperature (P-days) and relative humidity (RH) exceeded 52.5 and 525 for seven consecutive days (Singh *et al.*, 2016).

2.15.5 BLIGHTSIM

A mechanistic model (BLIGHTSIM) with an hourly time step was developed to simulate late blight in potato fields with changing meteorological variables and predict late blight outbreaks. BLIGHTSIM is an improved susceptible (S), latent (L), infectious (I), and removed (R) compartmental model that is driven by hourly temperature and relative humidity. Growth chamber data from a single infection cycle were used to calibrate the model, and field data were used to validate it. All of the analysed data sets had an excellent fit. According to growth chamber data on a single infection cycle, there was a substantial interaction between average temperature and its amplitude in their impacts on the area under the disease progress curve (AUDPC) (Narouei-Khandan *et al.*, 2020).

The management of late blight is complicated because it entails a number of factors that make decision-making difficult. Forecasting models can be incorporated into a Decision Support System to reduce this complication (DSS). The DSS is a system that interacts with users and enables them to make well-informed decisions to maximise the effectiveness of their crop protection strategy (Small *et al.*, 2015). Big Data Analysis, Artificial Intelligence, and Machine Learning are valuable tools in this context for attaining decision support. The most popular and significantly used machine learning algorithms for predicting potato late blight outbreaks are Artificial Neural Networks (ANN), Support Vector Machines (SVM), SVM Regression, and Logistic Regression.

2.16 Machine learning approach and its categories

Machine learning (ML) refers to a systematic study of algorithms and statistical models which are used by computers to accomplish a certain job without any precise programming (Mahesh, 2020). Machine learning is a scientific technique that enable computers to learn without explicit programming. There are four main categories of machine learning algorithms namely supervised, unsupervised, semi-supervised and reinforcement learning (Fig 2.5).

Supervised learning: It is a type of ML in which a function converts input to an output on the basis of illustrated input-output sets. It uses labelled training datasets made up of a collection of

training instances to deduce a function (Sarker, 2021). It is the most commonly used learning approach. These algorithms require external interventions as it is task driven. The popular supervised ML algorithms are – Decision tree, Naïve Bayes and support vector machine

Unsupervised learning: It is a type of ML that is used to analyse unlabelled data and external aid is not required. In general, it is data driven. This algorithm gathers useful information from input values only since precise output is unavailable in training set (Han *et al.*, 2022).

Semi-supervised learning: It is regarded as a combination of the supervised and unsupervised approaches outlined above because it uses both labelled and unlabelled datasets (Han *et al.*, 2022).

Reinforcement learning: In this kind of learning, model is not trained using any data. Trial and error approach is employed for learning by continuous interactions with the environment (Glielmo *et al.*, 2021). Hence it is driven by environment.

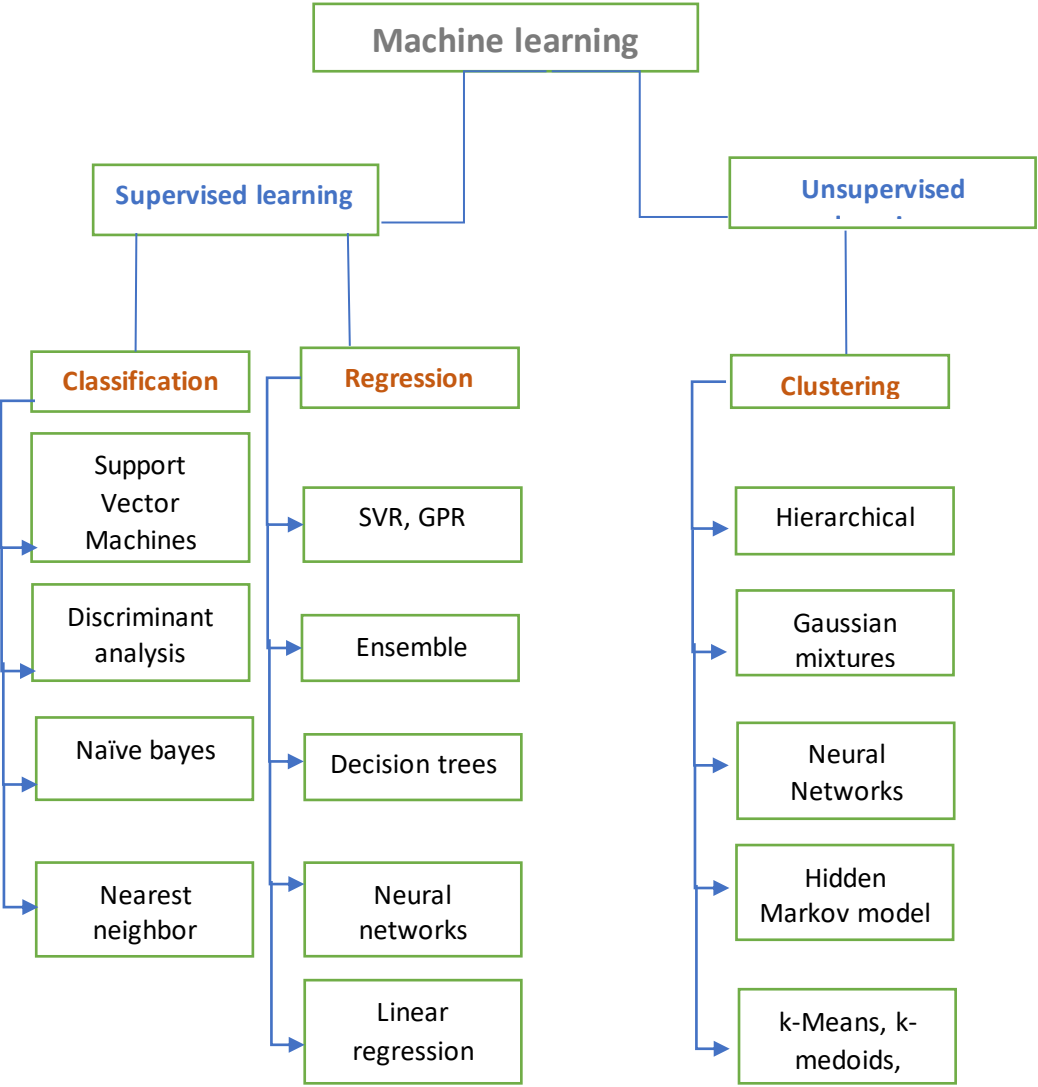


Fig. 2.5 Types of machine learning and their categories of algorithm

2.17 Need for machine learning in disease forecasting

Crop protection is essential for enhancement of agricultural productivity and for improvement of quality of the produce. Automatic disease detection in plants aids in early disease detection and suppression of disease, which improves agricultural productivity (Ushadevi, 2020). With emergence of precision agriculture, often known as digital agriculture, there has been a significant increase in the volume of data to be analysed. As a result, there is now a greater interest in the creation and application of algorithms that can use this data to analyse, organise, and ultimately speed or facilitate scientific advancement. Machine Learning (ML) along with big data technology and high-performance computation, has evolved to open up new possibilities for unravelling, quantifying, and comprehending data-intensive processes in agriculture (Liakos *et al.*, 2018). It is observed that machine learning is very effective in handling of the big data and improves the accuracy of prediction and reduces time taken in the process.

2.18 Application of machine learning techniques in disease forecasting

For the early detection of the powdery mildew in tomatoes, three weather-based prediction models were generated utilising the k-nearest neighbour (kNN), decision tree (DT), and random forest (RF) algorithms (Bhatia *et al.*, 2022). Based on meteorological data obtained from weather stations in Arpas, Hungary, Feed-forward Neural Network and Support Vector Machine Classification were used to predict the disease severity of late blight in Sardinia. A prediction model was developed for rice blast disease using recursive elimination algorithm for selecting important features for the disease and Auto-Sklearn and neural network algorithms for training the model (Hsieh *et al.*, 2019). In order to forecast powdery mildew disease in tomato, a hybrid Support Vector Machine (SVM) and Logistic Regression (LR) algorithm was developed in which previous data was supplied to an LR classifier, SVM was used to reduce noise from the raw data (Bhatia *et al.*, 2020). Many researchers have used machine learning techniques for forecasting plant diseases and each algorithm has its own advantages and disadvantages.

2.19 Effectiveness of Agrometeorological models

The implications of the change in climate on agriculture are unclear. Accurate weather forecasts and information on disease incidence are required to maximise the agricultural productivity and quality of the produce. Agriculture industry depends on the monsoon, hence reliable weather forecasts are in high demand. In one of the studies on accuracy of weather data for its application

in agriculture, Kumar, (2017) revealed that for agro-meteorological information to be useful, it must be accurate within a margin of 75%. Thus, efficacy of agrometeorological models depends on: (i) how accurately the original observations reflect the local conditions (ii) uniformity of local environment (iii) accuracy of observations made and (iv) sensitivity of model to agrometeorological variables (Branislava *et al.*, 2007).

The number of inputs in the model and the necessity to strike a balance between what is realistic in the field and accuracy of risk prediction are the important factors affecting effectiveness of the disease forecasting models (Rothmann and McLaren, 2018). The last decade of the 20th century saw an increase in the development of modelling tools and methodologies in all the fields of science and technology including agriculture (Dourado-Neto *et al.*, 1998). As the development and dissemination of disease is dependent on prevailing weather conditions hence knowledge of the weather is quite useful for development of forewarning models. Although several models are available for prediction of late blight of potato yet the region specificity of these models and less efficiency is a problem which needs to be tackled. Therefore, machine learning has a great scope in this field.

2.20 Need for the present study

For disease prediction in plant populations, many modelling techniques, such as neural networks and multiple regression, random forest etc. have been employed till date. However, in order to be used as decision support systems better understanding of the relation between plants, pathogens, and their environment, new prediction software must be utilized because the available systems are incapable of estimating the value of unknown data points and takes more time for training of models. However, Rothmann and McLaren, (2018) revealed that a balance has still not been achieved and that many forecasting models in agriculture including that of disease forecasting still need to be improved in order to achieve the desired qualities for farmer acceptance. Validation of models is complicated by the irregular nature of crop diseases. Many farmers are hesitant to use the decision-support technologies because the network to supply such tools to the agriculture industry is lacking, farmers find these unreliable, and they require too many input variables. Consequently, it is possible to create and commercialise more predictive models. The use of anticipatory projections by forecasting models could be crucial in making economically sound agronomic decisions in the future. Moreover, it is evident that locality-specific models must undergo adaptations before being used in a specific region.

3. MATERIALS AND METHODS

In this study models were developed on late blight disease in potato crop to forecast various disease parameters like Disease Severity (DS), Crop Age at First Appearance of Disease (CAFAD), Crop Age at Maximum Disease Severity (CAMDS), with data collected from published sources: All India Coordinated Research Project (AICRP) on Potato, using satellite-based weather parameters using machine learning approaches. The details and specifications of the materials and methods adopted during the course of investigation are presented in this chapter.

3.1 Objective 1: To establish relationship between weather variables and potato late blight disease incidence

Flow diagram depicting the activities undertaken under objective 1 is given in Fig 3.1.

3.1.1 Potato cultivar

Potato cultivar Kufri Chandramukhi was used in this study. It is an early maturing (mature 10 days earlier than up-to-date, 80-100 days), with attractive, oval, white tubers. It degenerates so slowly and keeps well in storage. It gives high yields and cooks easily and does not degenerate rapidly in the plains. Bihar, Gujarat, Haryana, Punjab, Madhya Pradesh, Himachal Pradesh, Uttar Pradesh, Orissa, and West Bengal are the main producers. This potato crop cultivar takes 80-90 days to develop. Large, round, white, somewhat flattened eyes, and white flesh that is dull. This potato has an average yield of 25 tonnes per acre. This potato is suitable for making instant flakes and chips. It is high yielding with slow rate of viral degeneration, wide adaptability and desirable commercial attributes, but it is susceptible to late blight

3.1.2 Potato late blight disease data collection

In the Annual Reports of AICRP (Potato), data on Monitoring the late blight in standing crops of potato have been reported through experiments conducted during summer/kharif seasons in hills/plateau and rabi season in the plains. There were 13 experiments in Crop Improvement, 20 in Crop Production and 19 in Crop Protection at various locations. In these reports the data collected from those experiments on Monitoring the late blight in standing crops of potato was collected, consolidated, analysed and compiled for the years 2006 to 2020.

Incidence and intensity of major potato pests and diseases were recorded in different locations throughout the country using “pest capture plot” technique. The locations selected were Bhubaneshwar, Chhindwara, Deesa, Dholi, Faizabad, Hassan, Hisar, Jalandhar, Jorhat, Kalyani,

Kanpur, Kota, Ooty, Pantnagar, Patna, Pasighat, Pune, Raipur, Shillong and Srinagar. The diseases recorded were late blight, early blight, Phoma leaf spot, bacterial wilt, mild mosaic, leaf roll, severe mosaic in standing crop and common scab, black scurf, and brown rot on harvest. Percent incidence and intensity of late blight disease on standing crop at 7 days, 14 days, 21 days and 28 days intervals after first appearance of disease and at harvest were recorded for all the varieties sown in different locations for each year and total tuber yield at maturity was calculated.

After analysing AICRP – Potato reports the most dreaded disease of potato viz. Late blight of potato, was selected for the present research work. From all the AICRP reports from year 2006 to 2020, first the locations for which disease data was available for all the years were selected and after that data on date of planting, date of harvesting, date of first appearance of disease and percentage disease severity at 7, 14, 21, and 28 days after first appearance of disease. This data was further used for formation of weighted indices and for development and validation of models.

3.1.2.1 Disease Severity (DS)

Disease severity refers to the percentage of organs or tissues of host plant showing the indications(symptoms) of disease. It depends on the quantity and size of the symptoms (Kranz, 1988). Formula used to calculate Disease severity index (DSI) as suggested by Chiang *et al.*, (2017) is

$$DSI (\%) = \frac{\sum(P * Q)}{(M * N)} * 100$$

Where P is severity score, Q is number of infected plants having the same score, M is total number of plants observed, N is maximum rating scale number. Information on percent disease severity for 7th, 14th, 21st and 28th day after first appearance of disease is collected from the reports and utilized in research work.

3.1.2.2 Crop Age at First Appearance of Disease (CAFAD)

It refers to age of the crop when it showed the first symptoms of disease. It is calculated by subtracting date of planting from date of first appearance of disease.

3.1.2.3 Crop Age at Maximum Disease Severity (CAMDS)

It refers to age of the crop when disease severity is at its peak. It is calculated by subtracting date of planting from date of maximum severity of disease (in our case date on 28th day after first appearance of disease).

3.1.3 Study Location

For the development of weather-based machine learning models for forecasting the above-mentioned disease parameters – disease severity (DS), Crop age at first appearance of the disease (CAFAD) and Crop age at maximum disease severity (CAMDS), of late blight disease in potato, depending on the data availability two locations namely Srinagar and Kalyani were selected.

Location Srinagar located in the North Western Himalayas is the summer capital of Jammu and Kashmir, India. It lies on the banks of the Jhelum River, a tributary of the Indus, and Dal and Anchar lakes in the Kashmir Valley. Srinagar has a humid subtropical climate (Köppen Cfa) with an average elevation of 1585m. The location has great variation in relief. The summer season is mild (July average temperature 5°C-30°C) but the winter season experiences severe cold conditions (January temperature 0°C to -4°C). The amount of average annual rainfall is 150 cm. Zonal arrangement in vegetation is found with varying heights along the hill slopes. Valleys and duns have thick layers of alluvium while hill slopes have thin brown hilly soils. The region has perennial streams due to high rainfall and snow-covered mountain peaks of Ganga, Yamuna, Jhelum, Chenab, Satluj and Beas. They provide irrigation water to canals and cheap hydel power for agriculture and industries. Maize, wheat, potato, barley are important crops. Temperate fruits like apples and pears are produced in some parts. Potato crop season in Srinagar is from 15 March to 31 July.

Location Kalyani is situated in the lower Gangetic plain, in Nadia district of West Bengal. Kalyani lies within the upper Ganges Delta along the east bank of the Hooghly River. Like many locations in the Indo-Gangetic Plain, the soil and water of Kalyani are predominantly alluvial in origin. Kalyani is located over the "Bengal basin", which is a pericratonic tertiary basin. Kalyani has a Tropical wet and dry or savanna climate (Classification: Aw) and has zero elevation from sea. Here the average amount of annual rainfall lies between 100 cm-200 cm. Temperature for July month varies from 26°C-41°C and for January month 9°C-24°C. The region has adequate storage of groundwater with a high-water table. Wells and canals are the main sources of irrigation. The problem of waterlogging and marshy lands is acute in some parts of the region. Rice is the main crop that at times yields three successive crops (Aman, Aus and Boro) in a year. Jute, maize, potato, and pulses are other important crops. Planning strategies include improvement in rice farming, horticulture (banana, mango and citrus fruits), pisciculture, poultry, livestock, forage production and seed supply. Potato crop season in Kalyani is from 15 Nov to 15 March.

3.1.4 Weather Data

To achieve the objectives of present investigation, long term weather data were collected from NASA powered web site SoDa _MERRA (Modern-Era Retrospective Analysis for Research and Applications version 2) for the locations Kalyani and Srinagar. Data collected on every 10 minutes were used calculate daily maximum and minimum temperature and morning and evening relative humidity, average wind speed, cumulative rainfall and solar radiations for each day. Daily weather data collected during the crop growth period for the two locations Kalyani and Srinagar during the last 15 years (2006 to 2020).

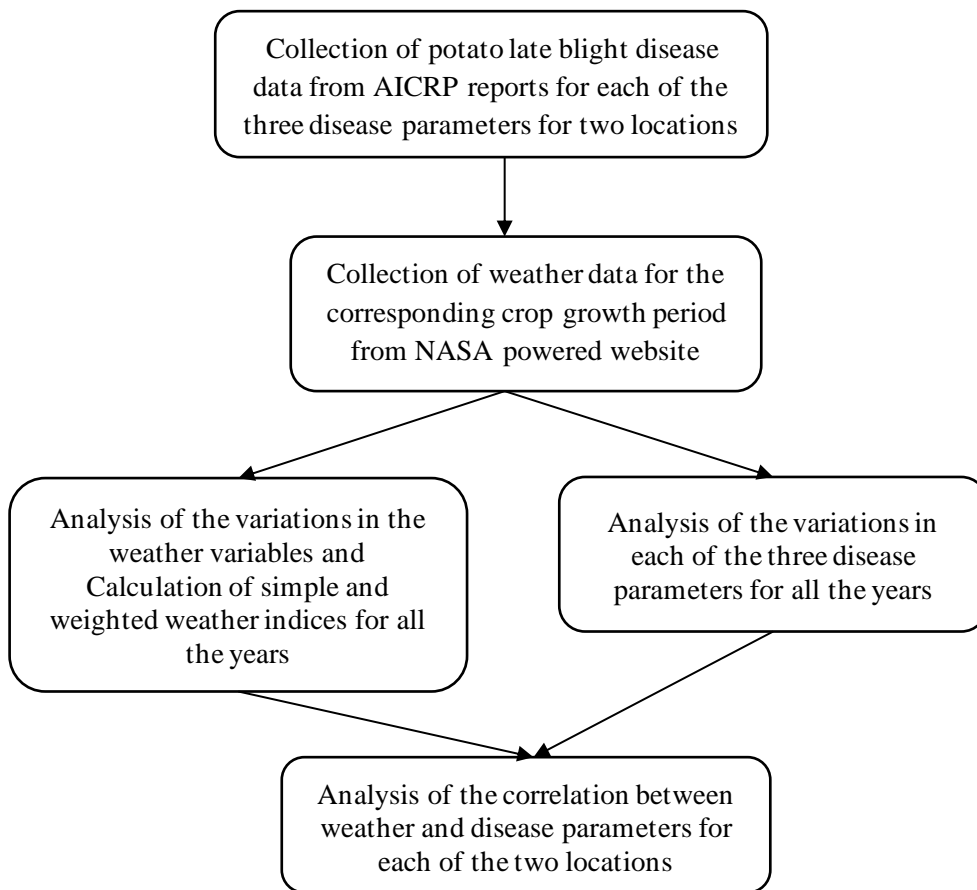


Fig. 3.1 Methodology followed in objective 1

3.1.5 Development of weather indices

Hendrick and Scholl (1943) model for distribution of weather elements, modified at Indian Agricultural Statistics Research Institute (IASRI), was used by researchers for forecasting various aspects viz. maximum disease severity/ pest population, time of first appearance, time of maximum pest population/ disease severity and weekly pest population/ disease severity for important pests and diseases of rice, mustard, pigeon pea, sugarcane, groundnut and cotton at various locations.

In this type of model, for each weather variable two types of indices were developed, one as simple total of values of weather variable in different weeks and other as a weighted total, weights being correlation coefficients between variable to forecast and weather variable in respective weeks. First index represents the total amount of weather variable during the period under consideration while the other takes care of distribution of weather variable with special reference to its importance in different period (day) in relation to the variables to forecast. On similar lines, indices were computed with products of weather variables (taken two at a time) for joint effects.

Indices calculation

$$Z_{ij} = \sum_{w=n_1}^{n_2} r_{iw}^j X_{iw}$$

X_{iw} is value of i^{th} weather variable in w^{th} day,

r_{iw} is correlation coefficient between variable to forecast and i^{th} weather variable in w^{th} day,

n_1 is initial day for which weather data are included in the model and

n_2 is final day for which weather data are included in the model

Weather data during the crop growth period was used to generate weather indices and to develop disease forecasting model. Weather indices used for developing disease forecasting model are given in Table 3.1

Table 3.1 Simple and Weighted indices used in models using composite weather variables

Simple Indices							
	Tmax	Tmin	RF	RH I	RH II	WS	SR
Tmax	Z10						
Tmin	Z120	Z20					
RF	Z130	Z230	Z30				
RH I	Z140	Z240	Z340	Z40			
RH II	Z150	Z250	Z350	Z450	Z50		
WS	Z160	Z260	Z360	Z460	Z560	Z60	
SR	Z170	Z270	Z370	Z470	Z570	Z670	Z70
Weighted Indices							
	Tmax	Tmin	RF	RH I	RH II	WS	SR
Tmax	Z11						
Tmin	Z121	Z21					
RF	Z131	Z231	Z31				
RH I	Z141	Z241	Z341	Z41			
RH II	Z151	Z251	Z351	Z451	Z51		
WS	Z161	Z261	Z361	Z461	Z561	Z61	
SR	Z171	Z271	Z371	Z471	Z571	Z671	Z71

Here

Z10- Sum of all daily maximum temperature

Z20- Sum of all daily minimum temperature

Z30- Sum of all daily rainfall

Z40- Sum of all daily morning relative humidity

Z50- Sum of all daily evening relative humidity

Z60- Sum of all daily wind speed

Z70- Sum of all daily solar radiation

3.2 Objective 2: To develop and validate weather-based forewarning models on severity of late blight in potato

Flow diagram depicting the activities undertaken under objective 2 is given in Fig 3.2.

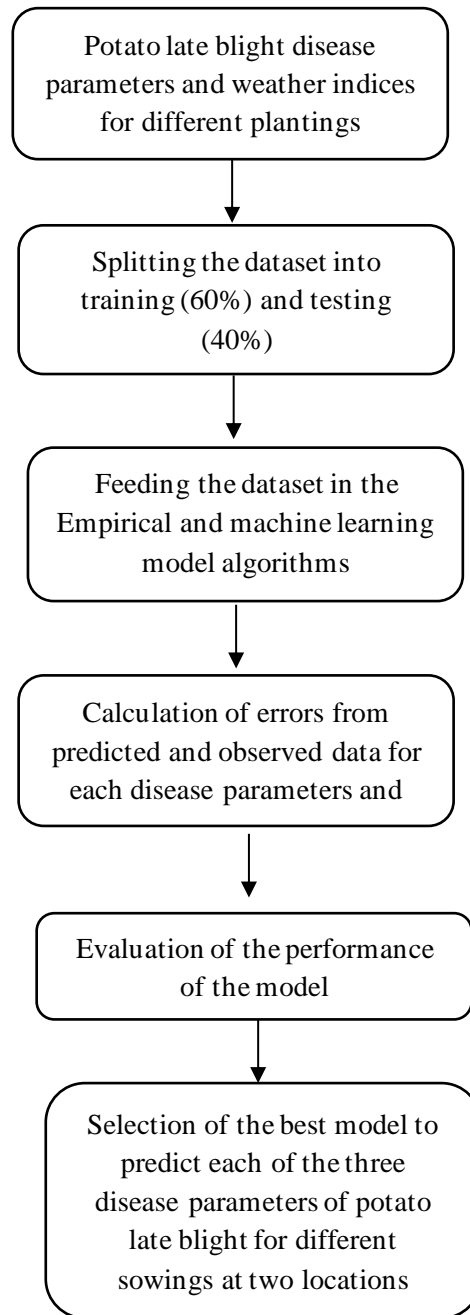


Fig. 3.2 Methodology followed in objective 2

3.2.1 Splitting dataset into training and testing

After development of weather indices these 56 indices along with the output parameter were divided into training and testing sets using random distribution approach. Out of the total 15 years data 10 years data were kept for development of the models and remaining 5 years data

were used for validation of the developed models. Following empirical models were used to see the impact of various weather indices of two locations.

3.2.2 Algorithms used for analysis

3.2.2.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) algorithm was designed by Vladimir N. Vapnik and Alexey Ya. Chervonenkis in the year 1963. It is a novel technique for time series forecasting and estimation. SVM is a widespread Supervised Learning algorithm, which is used for categorization and regression. Nevertheless, it is predominantly used in machine learning for classification purpose. SVM algorithm aims to construct the most fitting line that sets apart n-dimensional space in various groups so as to facilitate categorization of new data points in near future. This most fitting decisive borderline is known as hyperplane. SVM selects the extreme cases that facilitates generation of hyperplane. These extreme vectors are known as support vectors, and therefore algorithm is called as Support Vector Machine. The figure (Fig 3.3) given below shows the two contrasting classes categorised by a hyperplane.

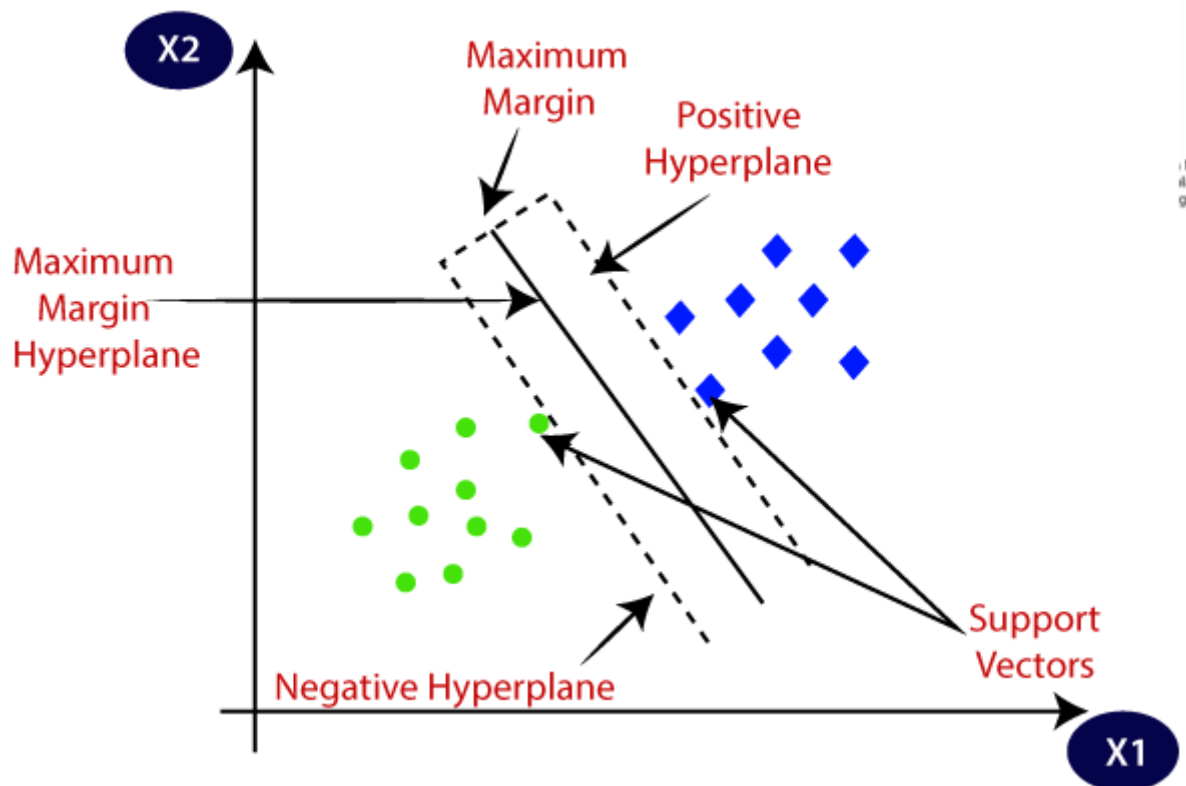


Fig 3.3 Two contrasting classes categorised by a hyperplane in SVM technique. Source: <https://www.javatpoint.com/machine-learning-support-vector-machine-algorithm>

For using SVM in R software, first the data was divided into training and testing sets and saved in .csv format and then the codes were run. The predicted and fitted values were obtained along with parameters for respective year. By comparing with the observed values R-squared, RMSE, nRMSE and MAPE were calculated and used to predict the accuracy of the model based on the error values.

3.2.2.2 Least Absolute Shrinkage and Selection Operator (LASSO)

Least Absolute Shrinkage and Selection Operator (LASSO) was proposed by Tibshirani. It is a statistical technique for the regularisation of data models and feature selection. Regularization is an important concept that is used to elude overfitting of the data, particularly when there is a considerable difference between data for training and testing. Lasso estimators are used for consistent regression coefficient and automatic variable selection. Lasso regression is a regularization approach. It is favoured more over regression methods to obtain a precise prediction. It uses shrinkage approach in which data points are narrowed towards a central point as the mean. For using LASSO in R software, first the data was imported and then codes were run as a result beta values and predicted values from LASSO were obtained. Using these beta values, an equation was formed and used to calculate predicted values by using the corresponding variables in the equation. Further errors were calculated using predicted and observed values which predict the accuracy of the model used.

3.2.2.3 Stepwise Multiple Regression model (SMLR)

Stepwise Multiple Regression model (SMLR) model was suggested for the first time by Fisher in the year 1924. This technique was later modified by Hendrick and Scholl (1943). The Stepwise approach of regression is a technique in which variables are added in a stepwise manner. For addition of data into the model there are two approaches namely forward selection and backward elimination approach. In this regression technique, variable's relative contributions are assessed and those variables which have insignificant contribution are removed from the model. In this study we have run SMLR in SPSS software, for this first the variables and data were added in the SPSS sheet and then analysed the data by selecting step wise in linear regression and at the end a syntax was obtained, from this syntax the best fitted equation for our data was obtained. Using this equation, the predicted output was obtained and using these along with the observed outputs the errors were calculated which determined the accuracy of SMLR model.

3.2.2.4 Hybrid machine learning approach for developing disease forecasting model

In this approach combination of two technique namely (i) LASSO with SVM and (ii) SMLR with SVM was attempted.

3.2.2.4a. Forecasting using combination of SVM- LASSO techniques

SVM- LASSO is a combination of variable selection method used for data analysis. In this method variables selected by LASSO techniques was used as an input variable for SVM. This was done to reduce the multi- collinearity problem which arise from weather variables. LASSO is a shrinkage technique effective for data reduction. It reduces the number of regressors to be used in SVM model. This helped to make the forecasting more precise. Here the variables selected by LASSO were used and SVM was run using these selected variables only and errors were calculated.

3.2.2.4b. Forecasting using combination of SMLR- SVM technique

SMLR- SVM is a combination of variable selection method used for data analysis. In this method variables selected by SMLR techniques were used as an input variable for SVM. This was done to reduce the multi- collinearity problem which arise from weather variables. SMLR a technique effective for data reduction. It reduced the number of regressors to be used in SVM model. This helped to make the forecasting more precise. In this approach variable selected from SMLR were used to train SVM model and errors were calculated using predicted and observed output.

3.2.3 Software used

3.2.3.1 R-software

R is a language and environment for statistical calculations. R provides a wide variety of statistical techniques such as linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering etc. For running LASSO model in R, HDCI (High Dimensional Confidence Interval) package was used and this package is based on LASSO and bootstrap whereas for training and testing the data for SVM, e1071 package was used which supplies functions for statistics and probabilistic algorithms

3.2.3.2 SPSS

SPSS stands for “Statistical Package for the Social Sciences”. It is an IBM tool. It was first launched in 1968. This package is mainly used for statistical analysis of the data. It provides data analysis for descriptive statistics, numeral outcome predictions, and identifying groups.

This software also provides data modification, graph plotting etc. for efficient and smooth management of data.

3.2.4 Error calculation

3.2.4.1 R²

R squared is a technique used in statistics which represents the proportion of variance in the dependent variable as explained by the independent variable (s) in regression. R-squared represents the goodness of fit of a regression model. The best possible value for R-squared is 1. If the values of R-squared is closer to 1, the fitted model is more accurate. R-squared is a comparison of residual sum of squares (SSR) with total sum of squares (SST).

3.2.4.2 RMSE

Root mean square error is the square root of the mean of the square of all of the errors. It is most often used to measure the difference between predicted values from the model and actual observed values from the experiment. RMSE is contemplated as an outstanding error metric used in numerical predictions. RMSE is a commendatory measure of accuracy, since it is dependent on scale therefore it can only be utilized for comparison of errors from different models and not for comparison between different variables within a model. it determines how efficiently a regression line fits the data points. The formula for calculation of RMSE is:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Predicted_i - Observed_i)^2}{N}}$$

where,

$Predicted_i$ = The predicted value for the i^{th} observation.

$Observed_i$ = The observed value for the i^{th} observation

N = Total number of observations.

3.2.4.3 nRMSE (Normalized Root Mean Square Error)

Normalized root mean square error is a measure of relative difference of estimated values versus observed values. For comparison of variables that are otherwise incomparable, approach of standardization is utilized which brings the variables on similar scales. This is facilitated by normalization of RMSE. Different formula for calculating normalized RMSE are as given below:

- Mean approach: $\text{NRMSE} = \text{RMSE}/y$
- Difference between maximum and minimum approach: $\text{NRMSE} = \text{RMSE}/(Y_{max} - Y_{min})$
- Standard deviation approach: $\text{NRMSE} = \text{RMSE}/\sigma$
- Interquartile range approach: $\text{NRMSE} = \text{RMSE}/(Q1 - Q3)$, i.e., the difference between 25th and 75th percentile.

In this study mean approach was used to calculate nRMSE.

3.2.4.4 MAPE

The Mean absolute percentage error (MAPE), also called as mean absolute percentage deviation (MAPD), is a statistical technique used to predict accuracy of a forecasting model. The mean absolute percentage error (MAPE) is the most commonly used measure for forecasting error, because of the reason that in this units are converted to percentage which makes it easily understandable. When there are no extremes or no zero values in the data points MAPE is the most accurate.

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{\text{actual}_i - \text{predicted}_i}{\text{actual}_i} \right|$$

4. RESULTS

4.1 Objective 1: To establish the relationship between weather parameters and potato late blight incidence

4.1.1 Climatic conditions of the location

4.1.1.1 Climatic conditions of Srinagar

Latitude of the location Srinagar is 34.084°N and longitude is 74.79°E and situated at an altitude of 1585m. As per Koppen's classification Srinagar has Humid subtropical climate. It falls under Agro-climatic zone - western Himalayan region. Summers in this region are warm and humid whereas winters are cold and dry. Average day time temperature during winters is 2.5 °C, night temperature falls below 0°C. Summers are comparatively warmer with average day time temperature of 24°C. Moderate to heavy rainfall occurs during winter season. Rainfall in the region is around 720mm.

4.1.1.2 Climatic conditions of Kalyani

Kalyani is located at an elevation of 11m, at a latitude of 22°58'30.31"N and a longitude of 88°26'4.23"E. Kalyani has a Tropical wet and dry or savanna climate (Classification: Aw). It falls under Agro-climatic zone - Lower Gangetic plains. Kalyani typically receives about 96.3 mm (3.79 inches) of precipitation. Day temperature varies from 28°C during December - January to around 40°C during April – May, whereas night temperature varies from 17°C in January to 29°C in June. Rainfall is the highest during July and August whereas almost nil during the months of December-January. Humidity all-round the year varies from 45-80% being the highest in the months of August, September and October but lowest during December-January.

4.1.2 Variation of weather parameters during potato crop growing season

4.1.2.1 Variation of weather parameters in Srinagar

4.1.2.1.1 Variation of weather parameters for early planting conditions in Srinagar

Analysing the weather parameters considered during the years 2006 – 2009 revealed that the maximum temperature varied from 20.88°C in 2008 to 11.57°C in 2020 (Fig 4.1a). Similar trend was observed for minimum temperature as well, which varied from 8.33°C in 2008 to 2.15°C in 2020. Cumulative rainfall was the highest during the year 2020 (509.721mm) and the lowest in year 2007 (150.869mm). Highest morning relative humidity (RH I) was observed in 2019 (82.96%) and lowest in 2006 (69.98%). Highest evening relative humidity (RH II) was

reported in 2020 (57.84%) and lowest in 2006 (27.42%). Highest wind speed was observed in 2008 (1.47m/s) and lowest in 2017 (1.02 m/s). Maximum solar radiation was received in 2007 (7396.65 W/m²) and minimum in 2020 (5539.679 W/m²).

4.1.2.1.2 Variation of weather parameters for normal planting condition in Srinagar

Maximum temperature varied from 22.65°C in 2008 to 13.50°C in 2020 and similar trend was observed for minimum temperature as well, which varied from 9.90°C in 2008 to 4.03°C in 2020 (Fig 4.1b). Cumulative rainfall was the highest in 2015 (771.249 mm) and lowest in 2006 (167.649 mm). Highest RH I was reported in year 2015 (83.13%) and lowest in 2006 (69.67%). Highest RH II was in year 2020 (56.47%) and lowest in 2006 (26.21%). Highest wind speed was observed in 2008 (1.57 m/s) and lowest in 2019 (1.05 m/s). Maximum solar radiation was received in 2006 (7694.78 W/m²) and minimum in 2020 (5797.71 W/m²).

4.1.2.1.1 Variation of weather parameters for late planting condition in Srinagar

Maximum temperature varied from 23.68°C in 2008 to 15.80°C in 2020 and similar trend was observed for minimum temperature, which varied from 11.32°C in 2008 to -9.0°C in 2012 (Fig 4.1c). Cumulative rainfall was the highest in 2015 (940.82 mm) and the lowest in 2006 (140.90 mm). Highest RH I was in 2010 (98.45%) and lowest in 2006 (70.12%). Highest RH II was in 2020 (53.69%) and lowest in 2006 (26.34%). Highest wind speed was reported in 2016 (1.39 m/s) and lowest in 2010 (0.96 m/s). Maximum solar radiation was received in year 2006 (7877.72 W/m²) and minimum in 2020 (6286.28 W/m²).

4.1.2.2 Variation of weather parameters in Kalyani

4.1.2.2.1 Variation of weather parameters for early planting conditions in Kalyani

Maximum temperature varied from 28°C in 2015 to 24°C in 2007 and minimum temperature varied from 14°C in 2015 to 9°C in 2012 (Fig 4.2a). Cumulative rainfall was the highest in 2006 (69.65 mm) and lowest in 2008 (0.67 mm). The highest morning relative humidity (RH I) was reported in 2007 (94.91%) and the lowest in 2012 (80.95%). The highest evening relative humidity (RH II) was observed in 2019 (49.58%) and the lowest in 2018 (31.18%). The highest wind speed was reported in 2012 (2.94m/s) and lowest in 2015 (1.77 m/s). The maximum solar radiation was received in 2016 (4475.40 W/m²) and the minimum in 2015 (4136.88 W/m²).

4.1.2.2.2 Variation of weather parameters for normal planting conditions in Kalyani

Maximum temperature varied from 28°C in 2015 to 24°C in 2007 and minimum temperature varied from 14°C in 2015 to 10°C in 2012 (Fig 4.2b). Cumulative rainfall was the highest in 2007 (68.31 mm) and the lowest in 2008 (0.42 mm). The highest RH I was reported in 2007

(94.07%) and the lowest in 2012 (77.54%). The highest RH II was reported in 2019 (47.77%) and the lowest in 2012 (28.92%). The highest wind speed was reported in 2012 (2.96m/s) and the lowest in 2015 (1.78 m/s). The maximum solar radiation was received in 2012 (4587.54 W/m²) and the minimum in 2015 (4128.34 W/m²).

4.1.2.2.3 Variation of weather parameters for late planting conditions in Kalyani

The maximum temperature varied from 28°C in 2016 to 24°C in 2007 and the minimum temperature varied from 14°C in 2015 to 10°C in 2012 (Fig 4.2c). Cumulative rainfall was the highest in 2006 (69.61mm) and the lowest in 2020 (0.49 mm). The highest RH I was observed in 2007 (92.92%) and the lowest RH I in 2012 (77.71%). The highest RH II was reported in 2007 (44.30%) and the lowest RH II in 2018 (28.37%). The highest wind speed was reported in 2012 (2.97m/s) and the lowest in 2015 (1.81 m/s). The maximum solar radiation was received in 2016 (4629.43 W/m²) and minimum in 2015 (4161.13 W/m²).

4.1.2 Late blight disease parameters in potato crop grown from 2006 to 2020

4.1.2.1 Late blight disease parameters in potato crop grown in Srinagar

4.1.2.1.1 Disease severity (DS) of late blight in potato crop in Srinagar

Disease severity (DS) of late blight in potato crop during the crop growing period during the years 2006 to 2020 for all plantings together was the lowest (17.2%) for early planting in 2011 to the maximum (49.6%) for late planting in 2010 (Fig 4.3). While for individual plantings the DS of potato late blight disease in early planting varied from 17.2 to 35.2%, the lowest and the highest severity were observed in 2011 and 2010 respectively with an average of 26.83% (Fig 4.3a). For normal planting DS ranged from 24 to 42.7% with the lowest and highest DS observed in 2008 and 2010 respectively with an average of 34.47% (Fig 4.3b). Under late planting variation in DS was from 30 to 49.6%, the lowest and the highest DS were observed in 2008 and 2010 respectively with an average of 40.6% (Fig 4.3c). Overall, when all plantings were considered together, the average DS was observed to be 34%, in Srinagar.

4.1.2.1.2 Crop age at first appearance of disease (CAFAD) in potato late blight in Srinagar

Crop age at first appearance of disease (CAFAD) for late blight in potato crop grown during 2006 to 2020, considering all plantings together, it varied from 50 DAS for late planting in 2020 to 102 DAS for late planting in 2015 (Fig 4.3). When individual plantings were considered the CAFAD, under early planting varied from 62 to 95 DAS, the lowest and highest were observed in 2016 and 2011 respectively with an average of 79 DAS (Fig 4.3a). Under normal planting,

CAFAD ranged from 55 to 95 DAS, the lowest and highest were observed in 2019 and 2015 respectively with an average of 79 DAS (Fig 4.3b). Under late planting, variation in CAFAD was from 50 to 102 DAS, the lowest and highest were observed in 2020 and 2015 respectively with an average of 80 DAS (Fig 4.3c). Overall average of CAFAD under all plantings was 79 DAS, in Srinagar.

4.1.2.1.3 Crop age at maximum disease severity (CAMDS) in potato late blight in Srinagar

Crop age at maximum disease severity (CAMDS) of late blight in potato crop grown during the years from 2006 to 2020, at Srinagar for all plantings considered together varied from 78 DAS for late planting in 2020 to 130 DAS for late planting in 2015 (Fig 4.3). While for the individual plantings the variation in CAMDS of late blight disease under early planting varied from 90 to 123 DAS, the minimum and the maximum CAMDS was observed in 2016 and 2011 respectively, with an average of 107 DAS (Fig 4.3a). Under normal planting CAMDS ranged from 83 to 123 DAS, the lowest and the highest were observed in 2019 and 2015 respectively, with an average of 107 DAS (Fig 4.3b). Under late planting variation in CAMDS was from 78 to 130 DAS, the lowest and the highest were observed in 2020 and 2015 respectively with an average of 108 DAS (Fig 4.3c). Overall, the average CAMDS, across all plantings was observed to be 107 DAS in Srinagar.

4.1.2.2 Late blight disease parameters in potato crop grown in Kalyani

4.1.2.2.1 Disease severity (DS) of late blight in potato crop at Kalyani

Disease severity (DS) in potato crop grown during the years from 2006 to 2020, for all plantings considered together varied from almost the nil in 2006, 2010, 2011, 2014, 2015, 2017 and 2020 to 100% in 2007 and 2008 (Fig 4.4). While for the individual plantings, the variation in DS of late blight disease under early planting varied from almost nil in 2006, 2010, 2011, 2014, 2015, 2017 and 2020 to 100% in 2007 and 2008, with an average of 42.3% (Fig 4.4a). Under normal planting, DS at Kalyani ranged from 40% in 2006, 2010, 2011, 2014, 2015, 2017 and 2020 to 100% in 2007 and 2008 with an average of 63.4% (Fig 4.4b). Under late planting, variation in DS was almost nil in 2006, 2010, 2011, 2014, 2015, 2017 and 2020 to 100% in 2007 and 2008, with an average of 45.34% (Fig 4.4c). Overall, under all plantings considered together the average DS was 50.3%, at Kalyani.

4.1.2.2.2 Crop age at first appearance of disease (CAFAD) late blight in potato crop at Kalyani

Crop age at first appearance of disease (CAFAD) of late blight in potato crop during the years 2006 to 2020 for all plantings considered together varied from 39 DAS for late planting during

2007 to 79 DAS for early planting in 2016 (Fig 4.4). While considering the individual planting the DS of late blight disease under early planting varied from 54 DAS in 2007 and 2008 to 79 DAS in 2016, with an average of 67 DAS (Fig 4.4a). Under normal planting the CAFAD ranged from 47 to 77 DAS, lowest and the highest were observed in 2019 and 2009 respectively, with an average of 60 DAS (Fig 4.4b). Under late planting variation in CAFAD was from 39 to 79 DAS, the minimum and maximum were observed in 2007 and 2009 respectively, with an average of 54 DAS (Fig 4.4c). Overall, when all planting were considered together, the average CAFAD was observed to be 60 DAS in Kalyani.

4.1.2.2.2 Crop age at maximum disease severity (CAMDS) late blight in potato crop at Kalyani

Crop age at maximum disease severity (CAMDS) of late blight in potato during the years 2006 to 2020, for all plantings together, varied from 67 DAS for late planting in 2007 to 107 DAS for early planting in 2016 (Fig 4.4). While for individual plantings the variation in CAMDS in late blight disease under early planting varied from 82 DAS in 2007 and 2008 to 107 DAS in 2016, with an average of 95 DAS (Fig 4.4a). For normal planting severity ranges from 75 DAS to 105 DAS for 2019 and 2009 respectively with an average CAMDS of 87 DAS (Fig 4.4b). Under late planting, the variation in CAMDS was from 67 to 107 DAS, the lowest and the highest observed in 2007 and 2009 respectively, with an average of 80 DAS (Fig 4.4a). Overall, while considering all planting together the average CAMDS was observed to be 87 DAS at Kalyani.

4.1.3 Correlation of disease parameters with weather parameters

Correlation of late blight disease parameters: disease severity (DS), CAFAD and CAMDS with weather parameters: maximum temperature, minimum temperature, rainfall, morning relative humidity, evening relative humidity, wind speed and solar radiation for three different plantings (early, normal and late) for the two locations (Srinagar and Kalyani) are shown in Table 4.1.

Table 4.1 Correlation of late blight disease parameters of potato crop with weather parameters (from 2006 to 2020), at two locations

Location Planting Parameter weather parameters			Tmax	Tmin	Rain	RH I	RH II	Wind speed	Solar radiation
Srinagar	Early	CAFAD	0.741**	0.746***	-0.091 ^{ns}	-0.457 ^{ns}	-0.638**	0.298 ^{ns}	0.711**
		CAMDS	0.741**	0.746***	-0.091 ^{ns}	-0.457 ^{ns}	-0.638**	0.298 ^{ns}	0.711**
		DS	0.197 ^{ns}	0.217 ^{ns}	-0.033 ^{ns}	-0.218 ^{ns}	-0.218 ^{ns}	-0.078 ^{ns}	0.184 ^{ns}
	Normal	CAFAD	0.699**	0.715**	0.130 ^{ns}	-0.159 ^{ns}	-0.520*	0.492 ^{ns}	0.585*
		CAMDS	0.699**	0.715**	0.130 ^{ns}	-0.159	-0.520*	0.492 ^{ns}	0.585*
		DS	-0.073 ^{ns}	-0.004 ^{ns}	0.231 ^{ns}	0.076 ^{ns}	0.083 ^{ns}	-0.171 ^{ns}	-0.032 ^{ns}
	Late	CAFAD	0.492 ^{ns}	-0.109 ^{ns}	0.557*	0.366 ^{ns}	-0.197 ^{ns}	0.042 ^{ns}	0.175 ^{ns}
		CAMDS	0.492 ^{ns}	-0.109 ^{ns}	0.557*	0.366 ^{ns}	-0.197 ^{ns}	0.042 ^{ns}	0.175 ^{ns}
		DS	-0.107 ^{ns}	-0.369 ^{ns}	0.340 ^{ns}	0.357 ^{ns}	0.119 ^{ns}	-0.237 ^{ns}	-0.086 ^{ns}
Kalyani	Early	CAFAD	0.696**	0.261 ^{ns}	-0.408 ^{ns}	-0.705**	-0.697**	0.187 ^{ns}	0.525*
		CAMDS	0.696**	0.261 ^{ns}	-0.408 ^{ns}	-0.705**	-0.697**	0.187 ^{ns}	0.525*
		DS	-0.335 ^{ns}	-0.264 ^{ns}	0.029 ^{ns}	0.272 ^{ns}	0.309 ^{ns}	0.238 ^{ns}	0.136 ^{ns}
	Normal	CAFAD	0.704**	0.256 ^{ns}	-0.223 ^{ns}	-0.766***	-0.751***	0.390 ^{ns}	0.565*
		CAMDS	0.704**	0.256 ^{ns}	-0.223 ^{ns}	-0.766***	-0.751***	0.390 ^{ns}	0.565*
		DS	-0.423 ^{ns}	-0.263 ^{ns}	0.327 ^{ns}	0.367 ^{ns}	0.455 ^{ns}	0.052 ^{ns}	0.046 ^{ns}
	Late	CAFAD	0.452 ^{ns}	0.279 ^{ns}	-0.279 ^{ns}	-0.350 ^{ns}	-0.448 ^{ns}	0.154 ^{ns}	0.369 ^{ns}
		CAMDS	0.425 ^{ns}	0.250 ^{ns}	-0.312 ^{ns}	-0.412 ^{ns}	-0.431 ^{ns}	0.173 ^{ns}	0.408 ^{ns}
		DS	-0.189 ^{ns}	-0.300 ^{ns}	0.121 ^{ns}	0.062 ^{ns}	0.169 ^{ns}	0.385 ^{ns}	0.243 ^{ns}

4.1.3.1 Correlation of disease parameters with weather parameters in Srinagar

4.1.3.1.1 Correlation of Disease severity (DS) of late blight with weather parameters for Srinagar

Correlation of Disease severity of late blight with weather parameters (averaged over the potato crop season in each year) in Srinagar for early planting is not found to be significant with any

of the weather parameters considered in this study. For normal and late planting also disease severity did not show any significant correlation with any of the weather parameters (Table 4.1).

4.1.3.1.2 Correlation of crop age at first appearance of disease (CAFAD) with weather parameters for Srinagar

Correlation of CAFAD with weather parameters during the cropping season in Srinagar under early planting condition was found to be positively correlated with maximum temperature (0.741**), minimum temperature (0.746**), and solar radiation (0.711**) (Table 4.1). However, it did not correlate significantly with any other weather parameters (rainfall, morning relative humidity, evening relative humidity and wind speed). For normal planting it correlated positively with minimum temperature (0.715**), maximum temperature (0.699**) and solar radiation (0.585*). For late planting CAFAD it correlated positively only with rainfall (0.557*).

4.1.3.1.3 Correlation of crop age at maximum disease severity (CAMDS) of late blight with weather parameters for Srinagar

Correlation of CAMDS with weather parameters during the potato cropping season in Srinagar for early planting significantly correlated well with maximum temperature (0.741**), minimum temperature (0.746**), and solar radiation (0.711**) and did not correlate well with other weather parameters like Rain, RH I, RH II and wind speed (Table 4.1). For normal planting it correlated significantly well with minimum temperature (0.715**) and maximum temperature (0.699**) and slightly with solar radiation (0.585*). For late planting CAFAD correlated with rainfall (0.557*) only.

4.1.3.1 Correlation of disease parameters with weather parameters in Kalyani

4.1.3.1.1 Correlation of Disease severity of late blight with weather parameters for Kalyani

Correlation of Disease severity (DS) of late blight with weather parameters during the potato cropping season in Kalyani for early, normal and late planting conditions was not significant (Table 4.1).

4.1.3.1.2 Correlation of crop age at first appearance of disease (CAFAD) with weather parameters for Kalyani

CAFAD during the cropping season in Kalyani for early planting was positively correlated with maximum temperature (0.696**) and solar radiation (0.525*) and negatively correlated with morning RH (-0.705**) and evening RH (-0.697**). Did not show significant correlation with rest of the weather parameters (Table 4.1). For normal planting CAFAD correlated significantly with maximum temperature (0.704**) and solar radiation (0.565*) and negatively correlated with

morning RH (-0.766**) and evening RH (-0.751**). For late planting CAFAD did not show significant correlation with any of the weather parameters.

4.1.3.1.3 Correlation of crop age at maximum disease severity (CAMDS) with weather parameters for Kalyani

Correlation of CAMDS with weather parameters during the potato cropping season in Kalyani for early planting was significant with maximum temperature (0.696**) and solar radiation (0.525*) and negatively with morning RH (-0.705**) and evening RH (-0.697**) did not correlate significantly with other parameters (Table 4.1). For normal planting it correlated significantly with maximum temperature (0.704**) and solar radiation (0.565*) and negatively correlated with morning RH (-0.766**) and evening RH (-0.751**). For late planting CAMDS did not correlate significantly with any of the weather parameters.

4.2 Objective 2: To develop and validate the weather-based forewarning model on incidence of late blight in potato.

4.2.1 Weather based prediction of potato late blight disease severity in two different locations under different planting

4.2.1.1 Weather based prediction of late blight disease severity in potato in Srinagar

4.2.1.1.1 Prediction of late blight disease severity (DS) under early planting for Srinagar

Models for predicting the disease severity of potato late blight for Srinagar location for early planting were developed using long term disease severity data along with daily weather data observed during crop growth period from 2006 to 2020 (Fig 4.5). Models developed had R² ranging between 0.957*** (SMLR-SVM) to 0.984*** (SVM). R² descended as 0.985*** (SVM), > 0.970*** (LASSO-SVM), > 0.969*** (LASSO), 0.959*** (SMLR) and 0.957*** (SMLR-SVM). RMSE for calibration ranged between 1.054 (SVM) and 1.781 (SMLR-SVM). Value of RMSE ascended as 1.054 (SVM), < 1.470 (LASSO-SVM), < 1.490 (LASSO), < 1.730 (SMLR) and 1.781 (SMLR-SVM). Mean absolute percentage error (MAPE) for calibration to predict late blight disease severity (DS) under early planting for Srinagar ranged between 7.588% (SVM) to 11.663 % (SMLR). Value of MAPE ascended as 7.588% (SVM), < 10.246 % (LASSO-SVM), < 10.308% (LASSO), < 11.643% (SMLR-SVM) and < 11.663 % (SMLR). nRMSE for calibration ranged between 0.066 (SVM) to 0.111 (SMLR-SVM).

Calibration and validation of the models developed for the weather-based prediction of disease severity of potato late blight using different techniques for early planting for Srinagar is shown in Table 4.2. RMSE for validation ranged between 1.478 (SMLR-SVM) to 6.717 (SVM). Value

of RMSE ascended as 1.478 (SMLR-SVM), < 1.594 (SMLR), < 1.676 (LASSO), < 2.409 (LASSO-SVM), and < 6.717 (SVM). Value of nRMSE for validation ranged between 0.078 (SMLR-SVM) and 0.354 (SVM). Value of nRMSE ascended as 0.078 (SMLR-SVM), < 0.084 (SMLR), < 0.088 (LASSO), < 0.127 (LASSO-SVM) and < 0.354 (SVM). MAPE for validation ranged between 8.429 % (LASSO) to 20.31% (SVM). Value of MAPE ascended as 8.429 % (LASSO) < 8.724 % (SMLR), < 8.752% (SMLR-SVM), < 10.120 % (LASSO-SVM), and < 20.31% (SVM). Among the models developed for disease severity model developed by SMLR-SVM technique performed best followed by SMLR, LASSO, LASSO-SVM.

The most important weather indices identified for prediction of disease severity under early planting for Srinagar by SMLR model (Table 4.3) were Z31 (sum of weighted rainfall), Z61 (sum of weighted wind speed), Z171 (sum of weighted maximum temperature*weighted solar radiation), and Z241 (sum of weighted minimum temperature*weighted morning relative humidity). While important weather indices identified by LASSO were Z10 (sum of daily maximum temperature), Z70 (sum of daily solar radiation), Z160 (sum of daily maximum temperature*daily wind speed), Z240 (sum of daily minimum temperature* morning relative humidity), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z61 (sum of weighted wind speed), Z161 (sum of weighted maximum temperature*weighted wind speed), Z171 (sum of weighted maximum temperature*weighted solar radiation), Z241 (sum of weighted minimum temperature*weighted morning relative humidity), Z271 (sum of weighted minimum temperature*weighted solar radiation), Z341 (sum of weighted rainfall*weighted morning relative humidity), Z361 (sum of weighted rainfall*weighted wind speed), Z461 (sum of weighted morning relative humidity*weighted wind speed).

Table 4.2 Weather based prediction of disease severity for early planting by different models for Srinagar

S N o	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (%)	nRMSE	MAPE (%)	RMSE	nRMSE	MAPE (%)
1	SVM	0.985***	1.054	0.066	7.588	6.717	0.354	20.311
2	LASSO	0.969***	1.490	0.093	10.308	1.676	0.088	8.429
3	SMLR	0.959***	1.730	0.108	11.663	1.594	0.084	8.742
4	LASSO-SVM	0.970***	1.470	0.092	10.246	2.409	0.127	10.120
5	SMLR-SVM	0.957***	1.781	0.111	11.643	1.478	0.078	8.752

Table 4.3 Equations for disease severity prediction of early planting for Srinagar location

Techniques used for developing model	Equation
SMLR	$20.138509 - 1.605E-007 * Z171 + 0.368 * Z61 - 9.951E-006 * Z241 + 0.083 * Z31$
LASSO	$-0.00102 * Z10 - 1.68E-08 * Z70 + 4.27E-05 * Z160 - 2.37E-06 * Z240 - 6.66E-05 * Z21 + 0.065649 * Z31 + 0.350371 * Z61 + 0.000284 * Z161 - 9.45E-08 * Z171 - 7.49E-06 * Z241 - 5.31E-08 * Z271 + 4.04E-05 * Z341 + 0.004151 * Z361 + 0.000108 * Z461 + 63.06163605$

4.2.1.1.2 Weather-based prediction of late blight disease severity (DS) prediction under normal planting for Srinagar

Models for predicting disease severity of late blight for Srinagar location for normal planting were developed using long term severity data along with daily weather data during crop growth period from 2006 to 2020 (Fig 4.6). Models developed had the R² ranging between 0.619^{***} (SVM) and SMLR-SVM) to 0.981^{***} (LASSO-SVM). Value of R² descended as 0.981^{***} (LASSO-SVM), > 0.958^{***} (SMLR), > 0.957^{***} (LASSO), > 0.930^{**} (SMLR-SVM) and > 0.619^{**} (SVM). RMSE for calibration ranged between 1.402 (LASSO-SVM) and 3.994 (SMLR). Value of RMSE ascended as 1.178 (SVM), < 1.402 (LASSO-SVM), < 2.681 (LASSO), < 2.701 (SMLR-SVM) and < 3.994 (SMLR). Mean absolute percentage error (MAPE) for calibration ranged between 6.935 % (LASSO-SVM) to 29.332 % (SMLR). Value of MAPE ascended as 6.935 % (LASSO-SVM), < 8.165 % (SVM), < 23.283 % (SMLR-SVM), < 23.839 % (LASSO), and 29.332 % (SMLR). Value of nRMSE for calibration ranged between 0.053 (SVM) to 0.181 (SMLR). Value of nRMSE ascends as 0.053 (SVM), 0.063 for LASSO-SVM, 0.121 for LASSO, 0.122 for SMLR-SVM and 0.181 for SMLR.

Calibration and validation of the models developed for the weather-based prediction of disease severity of potato late blight using different techniques for normal planting for Srinagar is shown in Table 4.4. RMSE for validation ranged between 4.865 (LASSO-SVM) and 51.203 (SMLR). Value of RMSE ascended as 4.865 (LASSO-SVM), < 5.149 (LASSO), < 10.375 (SVM), < 34.892 (SMLR-SVM), and < 51.203 (SMLR). Value of nRMSE for validation ranged between 0.186 (LASSO-SVM) to 1.970 (LASSO). Value of nRMSE ascended as 0.186 (LASSO-SVM), 0.396 (SVM), 1.333 (SMLR-SVM), 1.956 (SMLR), and 1.97 (LASSO). MAPE for validation ranged between 15.288 % (LASSO-SVM) to 23.880 % (SMLR). Value of MAPE ascended as 15.288 % (LASSO-SVM), < 16.202 % (LASSO), < 23.880 % (SMLR), < 23.880 % (SVM) and < 25.22 % (SMLR-SVM). Among the models developed for disease severity none of the models

performed well but out of these, model developed by LASSO-SVM technique had lowest nRMSE value (0.186).

The most important weather indices identified for prediction of disease severity under normal planting for Srinagar by SMLR model are Z470 (sum of daily morning relative humidity* daily solar radiation), Z31 (sum of weighted rainfall), Z121 (sum of weighted maximum temperature*weighted minimum temperature), Z461 (sum of weighted morning relative humidity*weighted wind speed) and Z471 (sum of weighted morning relative humidity*weighted solar radiation) (Table 4.5). While important weather indices identified by LASSO were Z70 (sum of daily solar radiation), Z240 (sum of daily minimum temperature* morning relative humidity), Z470 (sum of daily morning relative humidity*solar radiation), Z670 (sum of daily wind speed* daily solar radiation), Z31 (sum of weighted rainfall), Z51 (sum of weighted evening relative humidity), Z71 (sum of weighted solar radiation), Z151 (sum of weighted maximum temperature*weighted evening relative humidity), Z161 (sum of weighted maximum temperature*weighted wind speed), Z171 (sum of weighted maximum temperature*weighted solar radiation), Z251 (sum of weighted minimum temperature*weighted evening relative humidity), Z361 (sum of weighted rainfall*weighted wind speed), Z461 (sum of weighted morning relative humidity*weighted wind speed).

Table 4.4 Weather based prediction of disease severity for normal planting conditions by different models for Srinagar

S No	MODEL	Model accuracy during calibration parameters				Model accuracy parameters during validation		
		R ²	RMSE (%)	nRMSE	MAPE (%)	RMSE (%)	nRMSE	MAPE (%)
1	SVM	0.619***	1.178	0.053	8.165	10.375	0.396	23.880
2	LASSO	0.957***	2.681	0.121	23.839	5.149	1.97	16.202
3	SMLR	0.958***	3.994	0.181	29.332	51.203	1.956	23.880
4	LASSO-SVM	0.981***	1.402	0.063	6.935	4.865	0.186	15.288
5	SMLR-SVM	0.930***	2.701	0.122	23.283	34.892	1.333	72.225

Table 4.5 Equations for disease severity prediction under normal planting conditions for Srinagar location

Techniques used for developing model	Equation
SMLR	$8.2319+0.004*Z461-2.117E-007*Z470+0.072*Z31-1.340E-006*Z471-7.533E-006*Z121$
LASSO	$-6.87E-06*Z70-8.77E-06*Z240-2.93E-08*Z470-8.55E-06*Z670+0.059767*Z31+0.005023*Z51+0.000105*Z71-1.23E-06*Z161-4.11E-07*Z171-1.43E-05*Z251+0.005874*Z361+0.000989*Z461+37.35023942$

4.2.1.1.3 Weather-based prediction of late blight disease severity (DS) prediction under late planting for Srinagar

Models for predicting disease severity of late blight for Srinagar location under late planting conditions were developed using long term disease severity data along with daily weather data during crop growth period from 2006 to 2020 (Fig 4.7). Models developed had the R^2 ranging between 0.552*** to (SMLR) to 0.985*** for SVM. The value of R^2 ascends as 0.552*** (SMLR), < 0.774*** (SMLR-SVM), < 0.978*** (LASSO-SVM), < 0.978*** (LASSO) and < 0.985*** (SVM). RMSE for calibration ranged between 1.347 (SVM) to 9.583 (SMLR). Value of RMSE ascended as, 1.347 (SVM), < 1.637 (LASSO), < 1.650 (LASSO-SVM), < 5.286 (SMLR-SVM) and < 9.583 (SMLR). Mean absolute percentage error (MAPE) for calibration ranged between 16.638 % (SVM) to 70.890 % (SMLR). Value of MAPE ascended as 16.638 % (SVM), < 19.129% (LASSO), < 19.254 % (LASSO-SVM), < 41.917 % (SMLR-SVM) and < 70.890 % (SMLR). Value of nRMSE for calibration ranged between 0.050 (SVM) to 0.359 (SMLR). Value of nRMSE ascends as 0.050 (SVM), < 0.061 (LASSO), < 0.062 (LASSO-SVM), < 0.198 (SMLR-SVM) and < 0.359 (SMLR).

Calibration and validation of the models developed for the weather-based prediction of disease severity of potato late blight using different techniques for late plantings for Srinagar is shown in Table 4.6. RMSE for validation ranged between 5.332 (SMLR-SVM) to 12.161 (SMLR). Value of RMSE ascended as 5.332 (SMLR-SVM), < 5.337 (LASSO-SVM), < 5.530 (SVM), < 5.941 (LASSO) and < 12.161 (SMLR). Value of nRMSE for validation ranged between 0.174 (SMLR-SVM) and LASSO-SVM) to 0.397 (SMLR). Value of nRMSE ascended as 0.174 (LASSO-SVM and SMLR-SVM), < 0.180 (SVM) and LASSO-SVM), < 0.397 (SMLR) and < 0.194 (LASSO). MAPE for validation ranged between 14.291 % (SVM) to 32.154% (SMLR). Value of MAPE ascended as 14.291 % (SVM), < 15.201 % (SMLR-SVM), < 15.940 % (LASSO-SVM), < 16.880 % (LASSO) and < 32.154 % (SMLR). Among the models developed

for disease severity none of the models performed well but out of these, model developed by LASSO-SVM and SMLR-SVM technique had lowest nRMSE value (0.174).

The most important weather indices identified for prediction of disease severity under late planting for Srinagar by SMLR model were Z21 (sum of weighted minimum temperature), Z31 (sum of weighted daily rainfall), Z61 (sum of weighted wind speed), Z251 (sum of weighted minimum temperature* weighted evening relative humidity) (Table 4.7). While important weather indices identified by LASSO were Z10 (sum of daily maximum temperature), Z240 (sum of daily minimum temperature* daily morning relative humidity), Z11 (sum of weighted maximum temperature), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted daily rainfall), Z51 (sum of weighted evening relative humidity), Z71 (sum of weighted solar radiation), Z171 (sum of weighted maximum temperature* weighted solar radiation), Z251 (sum of weighted minimum temperature* weighted evening relative humidity), Z271 (sum of weighted minimum temperature* sum of weighted solar radiation), Z361 (sum of weighted rainfall * weighted wind speed), Z461 (sum of weighted morning relative humidity * weighted wind speed), Z471 (sum of weighted morning relative humidity* sum of weighted solar radiation), Z671 (sum of weighted wind speed * weighted solar radiation).

Table 4.6 Weather based prediction of disease severity for late planting by different models for Srinagar

SNo	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (%)	nRMSE	MAPE (%)	RMSE (%)	nRMSE	MAPE (%)
1	SVM	0.985***	1.347	0.050	16.638	5.530	0.180	14.291
2	LASSO	0.978***	1.637	0.061	19.129	5.941	0.194	16.880
3	SMLR	0.552***	9.583	0.359	70.890	12.161	0.397	32.154
4	LASSO-SVM	0.978***	1.650	0.062	19.254	5.337	0.174	15.940
5	SMLR-SVM	0.774***	5.286	0.198	41.917	5.332	0.174	15.201

Table 4.7 Equations for disease severity prediction under late planting conditions for Srinagar location

Techniques used for developing model	Equation
SMLR	$1.39009 - 2.037E-005 * Z251 + 0.019 * Z31 - 0.003 * Z21 + 0.237 * Z61$
LASSO	$-0.00243 * Z10 - 1.16E-05 * Z240 + 0.000394 * Z11 - 0.00078 * Z21 + 0.052069 * Z31 + 0.003887 * Z51 + 0.000157 * Z71 + 7.72E-08 * Z171 - 2.27E-05 * Z251 - 1.33E-08 * Z271 + 0.004105 * Z361 + 0.000326 * Z461 + 2.49E-07 * Z471 + 2.13E-05 * Z671 + 186.6563345$

4.2.1.1.4 Weather-based prediction of late blight disease severity (DS) prediction under all plantings (pooled data) for Srinagar

Models for predicting the severity of late blight for Srinagar location for all plantings pooled together were developed using long term disease severity data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig. 4.8). The model developed using Support Vector Regression (SVR), Least Absolute Shrinkage and Selection Operator (LASSO), Stepwise Multiple Linear Regressor (SMLR), variable selection by hybrid models LASSO-SVR and SMLR-SVR. Models developed had the R^2 ranging between 0.381*** (SVM) to 0.949*** (LASSO). Value of R^2 descended as 0.949*** (LASSO), > 0.938*** (LASSO-SVM), > 0.722*** (SMLR-SVM), > 0.704*** (SMLR) and > 0.381*** (SVM). RMSE for calibration ranged between 2.431 (LASSO) to 5.888 (SMLR). Value of RMSE ascended as 2.431 (LASSO), < 2.691 (LASSO-SVM), < 2.70 (SVM), < 5.711 (SMLR-SVM) and < 5.888 (SMLR). nRMSE for calibration ranged between 0.112 (LASSO) to 0.272 (SMLR). Value of nRMSE ascended as 0.112 (LASSO), < 0.122 (SVM), < 0.124 (LASSO-SVM), < 0.264 (SMLR-SVM) and < 0.272 (SMLR). MAPE ranged from 15.104% to 42.223%. Value of MAPE ascended as 15.104% (LASSO), < 16.916% (SVM), < 17.735% (LASSO-SVM), < 41.717% (SMLR) and < 42.223% (SMLR-SVM).

Calibration and validation of the models developed for the weather-based prediction of disease severity of potato late blight using different techniques for all plantings (pooled data) is shown in Table 4.8. RMSE for validation ranged between 5.585 (LASSO-SVM) to 19.365 (SMLR). Value of RMSE ascended as 5.585 (LASSO-SVM), < 6.873 (LASSO), < 8.687 (SVM), < 19.050 (SMLR-SVM), and 19.365 (SMLR). nRMSE for validation ranged between 0.221 (LASSO-SVM) to 0.766 (SMLR). Value of nRMSE ascended as 0.221 (LASSO-SVM), 0.272 (LASSO), 0.344 (SVM), 0.754 (SMLR-SVM) and 0.766 (SMLR). MAPE for validation ranged between 17.365% (LASSO-SVM) to 65.515% (SMLR). Value of MAPE 17.365 % (LASSO-SVM), 21.823% (LASSO), 24.79% (SVM), 52.125 % (SMLR-SVM) and 65.515 % (SMLR). Among the models developed for disease severity none of the models performed well but out of these, model developed by LASSO-SVM technique had lowest nRMSE value (0.221).

The most important weather indices identified for prediction of disease severity by SMLR model were Z240 (sum of daily minimum temperature* morning relative humidity), Z31 (sum of weighted rainfall), Z41 (sum of weighted morning relative humidity), Z141 (sum of weighted maximum temperature*weighted morning relative humidity), Z361(sum of weighted rainfall*weighted wind speed) (Table 4.9). While the important weather indices identified by LASSO were Z10 (sum of daily maximum temperature), Z50 (sum of daily evening relative humidity), Z240 (sum of daily minimum temperature* morning relative humidity), Z260 (sum

of daily minimum temperature* wind), Z270 (sum of daily minimum temperature* solar radiation), Z350 (sum of daily rainfall*evening relative humidity), Z360 (sum of daily rainfall*wind speed), Z450 (sum of daily morning relative humidity*evening relative humidity), Z11 (sum of weighted maximum temperature), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z51 (sum of weighted evening relative humidity), Z61 (sum of weighted wind speed), Z71 (sum of weighted solar radiation), Z151 (sum of weighted maximum temperature*weighted evening relative humidity), Z161 (sum of weighted maximum temperature*weighted wind speed), Z171 (sum of weighted maximum temperature*weighted solar radiation), Z241 (sum of weighted minimum temperature*weighted morning relative humidity), Z251 (sum of weighted minimum temperature*weighted evening relative humidity), Z261 (sum of weighted minimum temperature*weighted wind speed), Z271 (sum of weighted minimum temperature*weighted solar radiation), Z341 (sum of weighted rainfall*weighted morning relative humidity), Z351 (sum of weighted rainfall*weighted evening relative humidity), Z361 (sum of weighted rainfall*weighted wind speed), Z451 (sum of weighted morning relative humidity*weighted evening relative humidity), Z561 (sum of weighted evening relative humidity*weighted wind speed), Z671 (sum of weighted wind speed* weighted solar radiation)

Table 4.8 Weather based Prediction of disease severity for all plantings (pooled data) by different models for Srinagar

S N o	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (%)	nRMSE	MAPE (%)	RMSE (%)	nRMSE	MAPE (%)
1	SVM	0.381***	2.70	0.122	16.916	8.687	0.344	24.790
2	LASSO	0.949***	2.431	0.112	15.104	6.873	0.272	21.823
3	SMLR	0.704***	5.888	0.272	41.717	19.365	0.766	65.515
4	LASSO-SVM	0.938***	2.691	0.124	17.735	5.585	0.221	17.365
5	SMLR-SVM	0.722***	5.711	0.264	42.223	19.050	0.754	52.125

Table 4.9 Equation for disease severity prediction of all plantings (pooled data) for Srinagar location

Techniques used for developing model	Equation
SMLR	$51.599429+0.019*Z361+0.003*Z41+0.050*Z31-1.498E-005*Z240+7.118E-006*Z141$
LASSO	$0.016281*Z10+0.005588*Z50-2.28E-05*Z240-6.01E-06*Z260-6.37E-08*Z270-0.00025*Z350-0.0006*Z360+2.15E-06*Z450-0.00158*Z11-5.09E-05*Z21+0.04001*Z31+0.009793*Z51+0.020247*Z61+0.000128*Z71-6.18E-06*Z151-0.00127*Z161-1.75E-07*Z171-9.60E-06*Z241-1.92E-05*Z251+0.001206*Z261-2.98E-07*Z271+0.000238*Z341-3.53E-06*Z351+0.020025*Z361-4.31E-06*Z451+0.000426*Z561+6.60E-05*Z671-812.8699773$

4.2.1.2 Weather based prediction of late blight disease severity in Kalyani

4.2.1.2.1 Weather-based prediction of late blight disease severity (DS) prediction under early planting for Kalyani

Models for predicting disease severity of late blight for Kalyani location for early planting were developed using long term severity data along with daily weather data during crop growth period from 2006 to 2020 (Fig 4.9). Models developed had the R^2 ranged between 0.273^{ns} (SMLR) to 0.695^{***} (SVM). Value of R^2 descended as 0.695^{***} (SVM), > 0.434^{**} (LASSO), > 0.415^{**} (LASSO-SVM), > 0.381^{*} (SMLR-SVM) and > 0.273^{ns} (SMLR). RMSE for calibration ranged between 15.080 (SVM) to 25.506 (SMLR). Value of RMSE ascended as 15.080 (SVM), < 22.983 (LASSO-SVM), < 23.512 (SMLR-SVM), < 24.157 (LASSO) and < 25.506 (SMLR). Mean absolute percentage error for calibration ranged between 19.54 % (SMLR-SVM) to 162.452 % (LASSO). Value of MAPE ascended as 19.54 % (SMLR-SVM), < 90.764 % (SVM), < 121.899 % (LASSO-SVM), < 149.766 % (SMLR) and < 162.452 % (LASSO). Value of nRMSE for calibration ranged between 0.502 (SVM) to 0.849 (SMLR). Value of nRMSE ascends as 0.502 (SVM), < 0.765 (LASSO-SVM), < 0.783 (SMLR-SVM), < 0.804 (LASSO) and < 0.849 (SMLR).

Calibration and validation of the models developed for the weather-based prediction of disease severity of potato late blight using different techniques for early planting in Kalyani is shown in Table 4.10. RMSE for validation ranged between 9.093 (LASSO) to 31.340 (SVM). Value of RMSE ascended as 9.093 (LASSO), < 11.537 (SMLR-SVM) < 12.714 (SMLR), < 15.975

(LASSO-SVM) and < 31.340 (SVM). Value of nRMSE for validation ranged between 0.269 (LASSO) to 0.756 (SVM). Value of nRMSE ascended as 0.269 (LASSO), < 0.342 (SMLR-SVM), < 0.376 (SMLR), < 0.473 (LASSO-SVM) and < 0.756 (SVM). MAPE for validation ranged between 54.38 % (SMLR-SVM) to 115.871 % (SVM). Value of MAPE ascended as 54.380 % (SMLR- SVM), < 61.518 % (LASSO), < 74.950 % (SMLR), < 75.776 % (LASSO-SVM) and < 115.871 % (SVM). Among the models developed for disease severity none of the models performed well but out of these, model developed by LASSO technique had lowest nRMSE value (0.269).

The most important weather indices identified for prediction of disease severity under early planting in Kalyani, by SMLR model were Z21 (sum of weighted minimum temperature) and Z31 (sum of weighted rainfall) (Table 4.11). While important weather indices identified by LASSO model were Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z371 (sum of weighted rainfall*weighted solar radiation) and Z451(sum of weighted morning relative humidity*weighted evening relative humidity).

Table 4.10 Weather based prediction of disease severity under early planting condition by different models for Kalyani

S N	MODEL	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (%)	nRMSE	MAPE (%)	RMSE (%)	nRMSE	MAPE (%)
1	SVM	0.695***	15.080	0.502	90.764	31.340	0.756	115.871
2	LASSO	0.434**	24.157	0.804	162.452	9.093	0.269	61.518
3	SMLR	0.273 ^{ns}	25.506	0.849	149.766	12.714	0.376	74.950
4	LASSO-SVM	0.415**	22.983	0.765	121.899	15.975	0.473	75.776
5	SMLR-SVM	0.381*	23.512	0.783	19.540	11.537	0.342	54.380

Table 4.11 Equation for disease severity prediction under early planting conditions for Kalyani location

Techniques used for developing model	Equation
SMLR	$64.29+3.199*Z31-0.002*Z21$
LASSO	$-$ $0.00096*Z21+2.175488*Z31+0.0000828*Z371+0.000103*Z451+53.04$

4.2.1.2.2 Weather-based prediction of late blight disease severity (DS) prediction under normal planting for Kalyani

Models for predicting potato late blight disease severity for the location Kalyani under normal planting condition were developed using long term disease severity data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.10). Models developed had the $f R^2$ ranged from 0.006^{ns} (SVM) to 0.326* (SMLR). Value of R^2 was significant only for SMLR (0.326*). RMSE for calibration ranged between 15.873 (SVM) to 21.183 (SMLR-SVM). Value of RMSE ascended as 15.873 (SVM), < 17.950 (LASSO), < 19.721 (LASSO-SVM), < 20.243 (SMLR) and < 21.183 (SMLR-SVM). Mean absolute percentage error for calibration ranged between 13.29 % (SVM and LASSO-SVM) to 33.42 % (SMLR). Value of MAPE ascended as 13.289 % (SVM), < 22.873% (LASSO-SVM), < 23.791 % (SMLR-SVM), < 28.363 % (LASSO) and < 33.416 % (SMLR). Value of nRMSE for calibration ranged between 0.337 (SVM) to 0.450 (SMLR-SVM). Value of nRMSE ascends as 0.337 (SVM), < 0.382 (LASSO), < 0.419 (LASSO-SVM), < 0.430 (SMLR) and < 0.450 (SMLR-SVM).

Calibration and validation of the models developed for the weather-based prediction of disease severity of potato late blight using different techniques for all plantings at Kalyani are shown in Table 4.12. RMSE for validation ranged between 30.923 (LASSO) to 34.571 (SMLR-SVM). Value of RMSE ascended as 30.923 (LASSO), < 33.032 (SVM), < 32.688 (LASSO-SVM), < 33.856 (SMLR, and < 34.571 (SMLR-SVM). Value of nRMSE for validation ranged between 0.665 (LASSO) to 0.743 (SMLR-SVM). Value of nRMSE ascended as 0.665 (LASSO), < 0.703 (LASSO-SVM), < 0.710 (SVM), < 0.728 (SMLR) and < 0.743 (SMLR-SVM). MAPE for validation ranged between 146.390 % (SVM and LASSO-SVM) to 211.140 % (SMLR). Value of MAPE ascended as 146.390 % (SVM and LASSO-SVM), < 187.222 % (SMLR-SVM), < 199.432 % (LASSO) and < 211.140 % (SMLR). Among the models developed for disease severity none of the models performed well, however, model developed by LASSO technique had lowest nRMSE value (0.665).

The most important weather indices identified for prediction of disease severity by SMLR model was Z11 (sum of weighted maximum temperature) (Table 4.13). While important weather indices identified by LASSO model were Z450 (sum of daily morning relative humidity*daily evening relative humidity), Z11 (sum of weighted maximum temperature) and Z451 (sum of weighted morning relative humidity*weighted evening relative humidity).

Table 4.12 Weather based prediction of disease severity under normal planting conditions by different models for Kalyani

S N o	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (%)	nRMSE	MAPE (%)	RMSE (%)	nRMSE	MAPE (%)
1	SVM	0.006 ^{ns}	15.873	0.337	13.289	33.032	0.710	146.390
2	LASSO	0.291 ^{ns}	17.950	0.382	28.363	30.923	0.665	199.432
3	SMLR	0.326 [*]	20.243	0.430	33.416	33.856	0.728	211.140
4	LASSO-SVM	0.294 ^{ns}	19.721	0.419	22.873	32.688	0.703	186.988
5	SMLR-SVM	0.051 ^{ns}	21.183	0.450	23.791	34.571	0.743	187.222

Table 4.13 Equation for disease severity prediction under normal planting conditions for Kalyani location

Techniques used for developing model	Equation
SMLR	$47.131 + 0.004 * Z11$
LASSO	$0.0000128866422069243 * Z450 + 0.00141 * Z11 + 0.000246 * Z451 + 25.27$

4.2.1.2.3 Weather-based prediction of late blight disease severity (DS) prediction under late planting for Kalyani

Models for predicting potato late blight disease severity for Kalyani location under late planting were developed using long term disease severity data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.11). Models developed had the value of R² ranging between 0.140^{ns} (SMLR) to 0.556^{***} (SVM). Value of R² varied as 0.140^{ns} (SMLR), < 0.264^{ns} (SMLR-SVM), < 0.259^{ns} (LASSO), < 0.264^{ns} (LASSO-SVM) and < 0.556^{***} (SVM). RMSE for calibration ranged between 23.781 (SVM) to 32.142 (SMLR). Value of RMSE

ascended as, 23.781 (SVM), < 30.854 (LASSO-SVM), < 30.854 (SMLR-SVM), < 31.182 (LASSO) and < 32.142 (SMLR). Mean absolute percentage error for calibration ranged between 76.672 % (SVM) to 278.517 (SMLR). Value of MAPE ascended as 76.672% (SVM), < 156.617% (LASSO-SVM), < 156.617 (SMLR-SVM), < 273.900 % (LASSO), < 278.517 % (SMLR). Value of nRMSE for calibration ranged between 0.713 (SVM), to 0.964 (SMLR-SVM). Value of nRMSE ascends as 0.713 (SVM), < 0.935 (LASSO-SVM), < 0.925 (SMLR-SVM), < 0.925 (LASSO) and < 0.964 (SMLR).

Calibration and validation of the models developed for the weather-based prediction of disease severity of potato late blight using different techniques for all plantings at Kalyani is shown in Table 4.14. RMSE for validation ranged between 16.713 (SMLR) to 23.946 (LASSO). Value of RMSE ascended as 16.713 (SMLR), < 19.458 (SMLR-SVM), < 19.458 (LASSO-SVM), < 23.215 (SVM) and < 23.946 (LASSO). Value of nRMSE for validation ranged between 0.373 (SMLR) to 0.535 (LASSO). Value of nRMSE ascended as 0.373 (SMLR), < 0.435 (LASSO-SVM), < 0.435 (SMLR-SVM), < 0.519 (SVM) and < 0.535 (LASSO). MAPE for validation ranged between 89.381 % (LASSO-SVM) to 175.491 % (LASSO). Value of MAPE ascended as 89.381 % (LASSO-SVM and SMLR-SVM), < 93.610 % (SMLR), < 133.182 % (SVM) and < 175.491% (LASSO). None of the models performed well to predict disease severity for late planting at Kalyani based on the nRMSE value however, model developed by SMLR technique had lowest nRMSE value (0.373).

The most important weather indices identified for prediction of disease severity by SMLR model (Table 4.15) was Z21 (sum of weighted minimum temperature) and Z31 (sum of weighted rainfall), while indices identified by LASSO model were Z21 (sum of weighted minimum temperature) and Z31 (sum of weighted rainfall).

Table 4.14 Weather-based prediction of disease severity for late planting by different models for Kalyani

S N o	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (%)	nRMSE	MAPE (%)	RMSE (%)	nRMSE	MAPE (%)
1	SVM	0.556 ^{***}	23.781	0.713	76.672	23.215	0.519	133.182
2	LASSO	0.259 ^{ns}	31.182	0.935	273.900	23.946	0.535	175.491
3	SMLR	0.140 ^{ns}	32.142	0.964	278.517	16.713	0.373	93.610
4	LASSO-SVM	0.264 ^{ns}	30.854	0.925	156.617	19.458	0.435	89.381
5	SMLR-SVM	0.264 ^{ns}	30.854	0.925	156.617	19.458	0.435	89.381

Table 4.15 Equations for disease severity prediction of late planting for Kalyani location

Techniques used for developing model	Equation
SMLR	$-46.281 + 0.005 * Z_{21} + 2.416 * Z_{31}$
LASSO	$0.002538 * Z_{21} + 0.958967 * Z_{31} - 0.06$

4.2.1.2.4 Weather-based prediction of late blight disease severity (DS) prediction for all plantings (pooled together) for Kalyani

Models for predicting the potato late blight disease severity for the location Kalyani for all plantings (pooled data) were developed using long term disease severity data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.12). Models developed had the R² ranging between 0.006^{ns} (SMLR-SVM) to 0.423^{***} (SVM). Value of R² varied as 0.423^{***} (SVM), > 0.262^{**} (LASSO) and = 0.262^{**} (LASSO-SVM), > 0.091^{ns} (SMLR), > 0.006^{ns} (SMLR-SVM). RMSE for calibration ranged between 2.431 (LASSO) to 29.638 (SMLR-SVM). Value of RMSE ascended as 2.431 (LASSO), < 26.603 (LASSO-SVM), < 26.924 (SVM) < 28.914 (SMLR) and < 29.638 (SMLR-SVM). Mean absolute percentage error for calibration ranged between 15.104 % (LASSO) to 205.791% (SVM). Value of MAPE ascended as 15.104 % (LASSO), < 142.651 % (LASSO-SVM), < 153.827 % (SMLR-SVM), < 199.644 % (SMLR) and < 205.791 % (SVM). Value of nRMSE for calibration ranged between 0.112 (LASSO) to 0.869 (SVM). Value of nRMSE ascends as 0.112 (LASSO), < 0.723 (LASSO-SVM), < 0.785 (SMLR), < 0.805 (SMLR-SVM) and < 0.869 (SVM).

Calibration and validation of the models developed for the weather-based prediction of disease severity of potato late blight using different techniques for all plantings in Kalyani are shown in Table 4.16. RMSE for validation ranged between 8.687 (SVM) to 22.345 (SMLR). Value of RMSE ascended as 8.687 (SVM), < 19.286 (LASSO-SVM), < 19.365 (SMLR), < 20.182 (LASSO) and < 22.345 (SMLR-SVM). Value of nRMSE for validation ranged between 0.344 (SVM) to 0.766 (SMLR). Value of nRMSE ascended as 0.344 (SVM), < 0.465 (LASSO-SVM), < 0.487 (LASSO), < 0.539 (SMLR-SVM) and < 0.766 (SMLR). MAPE for validation ranged between 24.790 % (SVM) to 124.683% (LASSO). Value of MAPE ascended as 24.790 % (SVM), 65.515 % (SMLR). < 87.375 % (SMLR-SVM), < 97.527 % (LASSO-SVM), and 124.683 % (LASSO). Among the models developed to predict potato late blight disease severity for the location Kalyani for all plantings (pooled data), none of models performed well. however, model developed by SVM technique had the lowest nRMSE (0.344).

The most important weather indices identified for the prediction of potato late blight disease severity under all planting, by SMLR model (Table 4.17) were Z560 (sum of daily evening relative humidity*wind speed) and Z31 (sum of weighted rainfall). While important weather indices identified by LASSO model were Z370 (sum of daily rainfall* solar radiation), Z460 (sum of daily morning relative humidity*wind speed), Z21 (sum of weighted minimum temperature) and Z31 (sum of weighted rainfall), Z41 (sum of weighted morning relative humidity), Z371 (sum of weighted rainfall*weighted solar radiation) and Z451(sum of weighted morning relative humidity*weighted evening relative humidity).

Table 4.16 Weather based prediction of late blight disease severity in potato for all plantings (pooled data) at Kalyani

S N o	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (%)	nRMSE	MAPE (%)	RMSE	nRMSE	MAPE (%)
1	SVM	0.423***	26.924	0.869	205.791	8.687	0.344	24.790
2	LASSO	0.262**	2.431	0.112	15.104	20.182	0.487	124.683
3	SMLR	0.091 ^{ns}	28.914	0.785	199.644	19.365	0.766	65.515
4	LASSO-SVM	0.262**	26.603	0.723	142.651	19.286	0.473	97.527
5	SMLR-SVM	0.006 ^{ns}	29.638	0.805	153.827	22.345	0.535	87.375

Table 4.17 Equation for disease severity prediction of all planting (pooled data) for Kalyani location

Techniques used for developing model	Equation
SMLR	$6.155 + 2.018*Z31 + 0.004*Z560$
LASSO	$-0.000034*Z370 + 0.000913*Z460 - 0.00044*Z21 + 1.400393*Z31 + 0.007377*Z41 + 0.000279*Z371 + 0.0000622*Z451 + 26.41$

4.2.2 Weather based prediction of potato late blight crop age at first appearance of disease (CAFAD) in two different locations under different planting

4.2.2.1 Weather based prediction CAFAD of potato late blight in Srinagar

4.2.2.1.1 Weather based prediction CAFAD of potato late blight under early planting for Srinagar

Models for predicting crop age at first appearance of disease for Srinagar location for early planting were developed using long term CAFAD data along with daily weather data during crop growth period from 2006 to 2020 (Fig 4.13). Models developed had the value of R² ranging from 0.990*** (SMLR and SMLR-SVM) to 0.995*** (LASSO-SVM). Value of R² was in the decreasing order as 0.995*** (LASSO-SVM), > 0.994*** (LASSO), > 0.993*** (SVM), > 0.990*** (SMLR-SVM) and > 0.990*** (SMLR). RMSE for calibration ranged between 0.857 (LASSO-SVM) to 1.577 (SMLR). Value of RMSE ascended as 0.857 (LASSO-SVM), < 1.103 (LASSO), < 1.128 (SVM), < 1.187 (SMLR-SVM) and < 1.577 (SMLR). Mean absolute percentage error for calibration ranged between 1.011% (LASSO-SVM) to 1.722% (SMLR). Value of MAPE ascended as 1.011% (LASSO-SVM), < 1.098% (LASSO), < 1.211% (SMLR-SVM), < 1.300% (SVM) and < 1.722 % (SMLR). nRMSE for calibration ranged between 0.011 (LASSO-SVM) and 0.019 (SMLR). Value of nRMSE ascended as 0.011 (LASSO-SVM), < 0.014 (LASSO), < 0.014 (SVM), < 0.015 (SMLR-SVM) and < 0.019 (SMLR).

RMSE for validation ranged between 27.628 (SMLR-SVM) to 30.386 (LASSO-SVM). Value of RMSE ascended as 27.628 (SMLR-SVM), < 28.669 (SMLR), < 29.183 (LASSO), < 29.849 (SVM) and < 30.386 (LASSO-SVM). Value of nRMSE for validation ranged between 0.321 (SMLR-SVM) to 0.353 (LASSO-SVM). Value of nRMSE ascended as 0.321 (SMLR-SVM), < 0.333 (SMLR), < 0.333 (LASSO), < 0.346 (SVM) and < 0.353 (LASSO-SVM). MAPE for validation ranged between 23.080 % (SMLR-SVM) and 26.149 % (LASSO-SVM). Value of

MAPE ascended as 23.080% (SMLR-SVM), < 23.930 % (SMLR), < 25.245 % (LASSO), < 25.600% (SVM) and < 26.149 % (LASSO-SVM). Among the models developed to predict CAFAD of potato late blight at Srinagar under early planting, none of the models performed well however, model developed by SMLR-SVM technique had the lowest nRMSE value (0.321). Calibration and validation of the models developed to predict the CAFAD of potato late blight using different techniques at Srinagar under early planting is shown in Table 4.18

The most important weather indices identified for prediction of disease severity by SMLR model (Table 4.19) were Z11 (sum of weighted maximum temperature), Z21 (sum of weighted minimum temperature) while weather indices identified by LASSO are Z260 (sum of daily minimum temperature* wind), Z11 (sum of weighted maximum temperature), Z21 (sum of weighted minimum temperature), Z41 (sum of weighted morning relative humidity), Z261 (sum of weighted minimum temperature*weighted wind speed).

Table 4.18 Weather based prediction of crop age at first appearance of disease (CAFAD) for early planting by different models for Srinagar

S N	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.993***	1.128	0.014	1.300	29.849	0.346	25.600
2	LASSO	0.994***	1.103	0.014	1.098	29.183	0.339	25.245
3	SMLR	0.990***	1.577	0.019	1.722	28.669	0.333	23.930
4	LASSO-SVM	0.995***	0.857	0.011	1.011	30.386	0.353	26.149
5	SMLR-SVM	0.990***	1.187	0.015	1.211	27.628	0.321	23.080

Table 4.19 Equation for prediction of crop age at first appearance of disease (CAFAD) for early planting for Srinagar location

Techniques used for developing model	Equation
SMLR	$-46.59134 - 0.004 * Z21 + 0.013 * Z11$
LASSO	$-4.48E-06 * Z260 + 0.012596 * Z11 - 0.00202 * Z21 + 0.005619 * Z41 + 1.05E-07 * Z261 - 38.1617$

4.2.2.1.2 Weather based prediction of CAFAD of potato late blight under normal planting for Srinagar

Models for predicting crop age at first appearance of disease for Srinagar location for normal planting were developed using long term CAFAD data along with daily weather data during

potato crop growth period from 2006 to 2020 (Fig 4.14). Models developed had the value of R^2 ranging between 0.965*** (LASSO) to 0.996*** (SVM). Value of R^2 descended as 0.996*** (SVM), > 0.991*** (SMLR-SVM), > 0.991*** (SMLR), > 0.966*** (LASSO-SVM) and > 0.965*** (LASSO). RMSE for calibration ranged between 1.555 (SVM) and 3.977 (LASSO). Value of RMSE ascended as, 1.555 (SVM), < 1.695 (SMLR), < 2.026 (SMLR-SVM), < 3.299 (LASSO-SVM) and < 3.977 (LASSO). Mean absolute percentage error for calibration ranged between 1.642 % (SMLR) and 3.587 % (LASSO). Value of MAPE ascended as 1.642 % (SMLR), < 1.835 % (SVM), < 2.192 % (SMLR-SVM), < 3.239 % (LASSO-SVM) and < 3.587 % (LASSO). Calibration and validation of the models developed using different techniques to predict CAFAD of potato late blight at Srinagar under normal planting is shown in Table 4.20. Value of nRMSE for calibration ranged between 0.019 (SVM) and 0.048 (LASSO). Value of nRMSE ascends as 0.019 (SVM), < 0.020 (SMLR), < 0.024 (SMLR-SVM), < 0.040 (LASSO-SVM), and < 0.048 (LASSO).

RMSE for validation ranged between 6.002 (LASSO) and 46.457 (SVM). Value of RMSE ascended as 6.002 (LASSO), < 33.047 (LASSO-SVM), < 38.911 (SMLR-SVM), < 41.552 (SMLR) and < 46.457 (SVM). Value of nRMSE for validation ranged between 0.079 (LASSO) and 0.615 (SVM). Value of nRMSE ascended as 0.079 (LASSO), < 0.437 (LASSO-SVM), < 0.515 (SMLR-SVM), 0.550 (SMLR) and < 0.615 (SVM). MAPE for validation ranged between 10.53 % (LASSO) and 27.973 % (SVM). Value of MAPE ascended as 7.420 % (LASSO), < 21.209 % (LASSO-SVM), < 23.099 % (SMLR-SVM), < 25.535 % (SMLR) and < 27.973 % (SVM). Among the models developed to predict CAFAD of potato late blight at Srinagar under normal planting, the model developed by LASSO technique performed the best having nRMSE of 0.079. All other models developed showed higher nRMSE value.

The most important weather parameters identified for prediction of disease severity by SMLR model (Table 4.21) were Z21 (sum of weighted minimum temperature), Z241 (sum of weighted minimum temperature*weighted morning relative humidity), Z561 (sum of weighted evening relative humidity*weighted wind speed). While indices identified by LASSO were Z21 (sum of weighted minimum temperature), Z41 (sum of weighted morning relative humidity), Z71 (sum of weighted solar radiation).

Table 4.20 Weather based prediction of crop age at first appearance of disease (CAFAD) for normal planting by different models for Srinagar

S N	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.996***	1.555	0.019	1.835	46.457	0.615	27.973
2	LASSO	0.965***	3.977	0.048	3.587	6.002	0.079	7.420
3	SMLR	0.991***	1.695	0.020	1.642	41.552	0.550	25.535
4	LASSO-SVM	0.966***	3.299	0.040	3.239	33.047	0.437	21.209
5	SMLR-SVM	0.991***	2.026	0.024	2.192	38.911	0.515	23.099

Table 4.21 Equation for prediction of crop age at first appearance of disease (CAFAD) for normal planting for Srinagar location

Techniques used for developing model	Equation
SMLR	$7.58337-0.019*Z21-0.009*Z561+4.087E-005*Z241$
LASSO	$-0.01097*Z21+0.013084*Z41+0.000153*Z71-2.26959$

4.2.2.1.3 Weather based prediction of CAFAD of potato late blight under late planting for Srinagar

Model for predicting crop age at first appearance of disease for Srinagar location under late planting condition were developed using long term CAFAD data along with daily weather data during crop growth period from 2006 to 2020 (Fig 4.15). Models developed had the value of R² ranging between 0.733*** (LASSO) and 0.996*** (SMLR). Value of R² ascends as 0.733*** (LASSO), < 0.919*** (LASSO-SVM), < 0.926*** (SMLR-SVM), < 0.927*** (SVM) and < 0.996*** (SMLR). Calibration and validation of the models developed using different techniques for predicting crop age at first appearance of disease for Srinagar location under late planting condition is shown in Table 4.22. RMSE for calibration ranged between 1.065 (SMLR) and 10.273 (LASSO). Value of RMSE ascended as, 1.065 (SMLR), < 1.289 (SMLR-SVM), < 1.689 (SVM), < 2.141 (LASSO-SVM) and < 10.273 (LASSO). Mean absolute percentage error for calibration ranged between 0.999 % (SMLR) to 11.742 % (LASSO). Value of MAPE ascended as 0.999 % (SMLR), < 1.263 % (SMLR-SVM), < 2.133% (SVM), < 2.344% (LASSO-SVM), and < 11.742 % (LASSO). Value of nRMSE for calibration ranged between 0.013 (SMLR) and

0.127 (LASSO). Value of nRMSE ascended as 0.013 (SMLR), < 0.016 (SMLR-SVM), < 0.021 (SVM), < 0.026 (LASSO-SVM) and < 0.127 (LASSO).

RMSE for validation ranged from 8.040 (LASSO-SVM) to 46.529 (LASSO). Value of RMSE ascended as 8.040 (LASSO-SVM), < 31.820 (SVM), < 31.836 (SMLR-SVM), < 33.003 (SMLR) and < 46.529 (LASSO). Value of nRMSE for validation ranged between 0.102 (LASSO-SVM) to 0.587 (LASSO). Value of nRMSE ascended as 0.102 (LASSO-SVM), < 0.402 (SMLR-SVM and SVM), < 0.417 (SMLR) and < 0.587 (LASSO). MAPE for validation ranged between 5.498 % (LASSO-SVM) to 60.691% (LASSO). Value of MAPE ascended as 5.498 % (LASSO-SVM), < 18.988% (SMLR-SVM), < 20.224% (SMLR), < 22.204% (SVM) and < 60.691% (LASSO). Among the models developed for prediction potato late blight disease severity at Srinagar under late planting conditions, model developed by LASSO-SVM technique performed the best having nRMSE value of 0.102 while models developed by other techniques had higher nRMSE values.

The most important weather indices identified for prediction of potato late blight disease severity under planting conditions at Srinagar by SMLR model (Table 4.23) were Z21 (sum of weighted minimum temperature), Z360 (sum of daily rainfall * daily wind speed). While important weather indices identified by LASSO were Z21 (sum of weighted minimum temperature), Z41 (sum of weighted morning relative humidity).

Table 4.22 Weather based prediction of crop age at first appearance of disease (CAFAD) for late planting by different models for Srinagar

S N	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.927***	1.689	0.021	2.133	31.820	0.402	22.204
2	LASSO	0.733***	10.273	0.127	11.742	46.529	0.587	60.691
3	SMLR	0.996***	1.065	0.013	0.999	33.003	0.417	20.224
4	LASSO-SVM	0.919***	2.141	0.026	2.344	8.040	0.102	5.498
5	SMLR-SVM	0.926***	1.289	0.016	1.263	31.836	0.402	18.988

Table 4.23 Equation for prediction of crop age at first appearance of disease (CAFAD) under late planting for Srinagar location

Techniques used for developing model	Equation
SMLR	27.782236-0.015*Z21+0.005*Z360
LASSO	-0.01068*Z21+0.008494*Z41+44.9519

4.2.2.1.4 Weather based prediction of CAFAD of potato late blight for all plantings (pooled together) for Srinagar

Models for predicting crop age at first appearance of disease (CAFAD) for Srinagar location for all three different plantings pooled together were developed using long term CAFAD data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.16). Models developed had the R^2 ranging between 0.138^{ns} (SMLR) to 0.949^{***} (SVM). Value of R^2 descended as 0.949^{***} (SVM), > 0.934^{***} (LASSO), > 0.934^{***} (LASSO-SVM), > 0.929^{***} (SMLR-SVM) and > 0.138^{ns} (SMLR). Calibration and validation of the models developed using different techniques for all plantings is shown in Table 4.24. RMSE for calibration ranged between 3.640 (SVM) and 82.234 (SMLR). Value of RMSE ascended as 3.640 (SVM), < 4.133 (LASSO-SVM), < 4.226 (LASSO), < 4.354 (SMLR-SVM) and < 82.234 (SMLR). Mean absolute percentage error for calibration ranged between 2.849% (SVM) and 79.716 % (SMLR). Value of MAPE ascended as 2.849 % (SVM), < 3.773% (LASSO-SVM), < 4.05% (SMLR-SVM), < 4.237% (LASSO) and < 79.716 % (SMLR). nRMSE for calibration ranged between 0.045 (SVM) and 1.008 (SMLR). Value of nRMSE ascended as 0.045 (SVM), < 0.051 (LASSO-SVM), < 0.052 (LASSO), < 0.053 (SMLR-SVM) and < 1.008 (SMLR).

RMSE for validation ranged between 19.489 (SMLR-SVM) to 170.584 (SMLR). Value of RMSE ascended as 19.489 (SMLR-SVM), < 22.820 (LASSO), < 23.63 (LASSO-SVM), < 31.754 (SVM) and < 170.584 (SMLR). Value of nRMSE for validation ranged between 0.243 (SMLR-SVM) and 2.123 (SMLR). Value of nRMSE ascended as < 0.243 (SMLR-SVM), < 0.284 (LASSO), < 0.294 (LASSO-SVM), < 0.395 (SVM) and < 2.123 (SMLR). MAPE for validation ranged between 14.173% (SMLR-SVM) and 188.784 % (SMLR). Value of MAPE ascended as 14.17% (SMLR-SVM), < 17.088% (LASSO-SVM), < 21.473% (SVM), < 17.162 % (LASSO) and < 188.784 % (SMLR). Among the models developed for CAFAD none of the models performed well however model developed by SMLR-SVM technique had the lowest nRMSE value (0.243).

The most important weather indices identified for prediction of disease severity by SMLR model (Table 4.25) were Z270 (sum of daily minimum temperature* solar radiation), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z161 (sum of weighted maximum temperature* weighted wind speed), Z371(sum of weighted rainfall*weighted solar radiation) while parameters identified by LASSO are Z10 (sum of daily maximum temperature), Z240 (sum of daily minimum temperature* morning relative humidity), Z270 (sum of daily minimum temperature* solar radiation), Z11 (sum of weighted maximum temperature), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z61 (sum of weighted wind speed), Z121 (sum of weighted maximum *weighted minimum temperature), Z141 (sum

of weighted maximum temperature*weighted morning relative humidity), Z461 (sum of weighted morning relative humidity*weighted wind speed).

Table 4.24 Weather based prediction of crop age at first appearance of disease (CAFAD) for all plantings (pooled data) by different models for Srinagar

S N	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.949***	3.640	0.045	2.849	31.754	0.395	21.473
2	LASSO	0.934***	4.226	0.052	4.237	22.820	0.284	17.162
3	SMLR	0.138 ^{ns}	82.234	1.008	79.716	170.584	2.123	188.784
4	LASSO-SVM	0.934***	4.133	0.051	3.773	23.630	0.294	17.088
5	SMLR-SVM	0.929***	4.354	0.053	4.050	19.489	0.243	14.173

Table 4.25 Equation for prediction of crop age at first appearance of disease (CAFAD) of all planting dates for Srinagar location

Techniques used for developing model	Equation
SMLR	$150.8119 - 0.009 * Z_{21} + 0.001 * Z_{161} - 1.248 * Z_{61} + 2.49 * Z_{31} - 5.179E-006 * Z_{371} - 3.624E-007 * Z_{270}$
LASSO	$-0.00529 * Z_{10} - 2.36E-06 * Z_{240} - 1.37E-07 * Z_{270} - 0.00086 * Z_{11} - 0.00848 * Z_{21} + 0.173935 * Z_{31} - 1.07027 * Z_{61} - 1.51E-05 * Z_{121} + 1.80E-06 * Z_{141} + 0.001023 * Z_{461} + 314.2222$

4.2.2.2 Weather based prediction CAFAD of potato late blight in Srinagar

4.2.2.2.1 Weather based prediction CAFAD of potato late blight under early planting for Kalyani

Models for predicting crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location under early planting conditions were developed using long term CAFAD data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.17). Models developed had the R² ranging from 0.077^{ns} (LASSO) to 0.989*** (SVM). Value of R² ascended as 0.077^{ns} (LASSO), < 0.844*** (LASSO-SVM), < 0.889*** (SMLR-SVM), < 0.889*** (SMLR) and < 0.989*** (SVM). Calibration and validation of the models developed using different techniques to predict crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location under early planting conditions is shown in Table 4.26. RMSE for calibration ranged between 0.744 (SVM) to 7.575 (LASSO). Value of RMSE ascended as, 0.744

(SVM), < 2.373 (SMLR), < 2.440 (SMLR-SVM), < 2.796 (LASSO-SVM) and < 7.575 (LASSO). Mean absolute percentage error for calibration ranged between 1.104 % (SVM) to 9.914 (LASSO). Value of MAPE ascended as 1.104% (SVM), < 2.669% (LASSO-SVM), 2.856% (SMLR-SVM), < 2.915% (SMLR) and < 9.914 (LASSO). Value of nRMSE for calibration ranged between 0.011 (SVM), and 0.111 (LASSO). Value of nRMSE ascended as 0.011 (SVM), < 0.035 (SMLR), < 0.036 (SMLR-SVM), < 0.041 (LASSO-SVM) and < 0.111 (LASSO).

RMSE for validation ranged between 2.053 (SMLR) to 6.570 (SVM). Value of RMSE ascended as 2.053 (SMLR), < 2.808 (SMLR-SVM), < 3.444 (LASSO), < 4.056 (LASSO-SVM) and < 6.570 (SVM) (Table 4.26). Value of nRMSE for validation ranged between 0.032 (SMLR) to 0.102 (SVM). Value of nRMSE ascended as 0.032 (SMLR), < 0.044 (SMLR-SVM), < 0.061 (LASSO), < 0.063 (LASSO-SVM) and < 0.102 (SVM). MAPE for validation ranged between 2.283% (SMLR) and 8.176% (SVM). Value of MAPE ascended as 2.283 % (SMLR) < 4.360 % (SMLR-SVM), < 5.020% (LASSO), < 5.607 % (LASSO-SVM) and < 8.176 % (SVM). Among the models developed for predicting crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location under early planting conditions, the model developed by SMLR technique performed best followed by SMLR-SVM, LASSO-SVM, and SVM based on the nRMSE value.

The most important weather indices identified for prediction of disease severity by SMLR model (Table 4.27) were Z10 (sum of daily maximum temperature) and Z11 (sum of weighted maximum temperature). While the important weather indices identified by LASSO model were Z370 (sum of daily rainfall* solar radiation), Z460 (sum of daily morning relative humidity*daily wind speed), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z41 (sum of weighted morning relative humidity), Z371(sum of weighted rainfall* weighted solar radiation) and Z451 (sum of weighted morning relative humidity*weighted evening relative humidity).

Table 4.26 Weather based prediction of crop age at first appearance of disease (CAFAD) under early planting conditions by different models for Kalyani location

SN	MODEL	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.989***	0.744	0.011	1.104	6.570	0.102	8.176
2	LASSO	0.077 ^{ns}	7.575	0.111	9.914	3.444	0.061	5.020
3	SMLR	0.889***	2.373	0.035	2.915	2.053	0.032	2.283
4	LASSO-SVM	0.844***	2.796	0.041	2.669	4.056	0.063	5.607
5	SMLR-SVM	0.889***	2.440	0.036	2.856	2.808	0.044	4.360

Table 4.27 Equations for prediction of crop age at first appearance of disease (CAFAD) for early planting for Kalyani location

Techniques used for developing model	Equation
SMLR	$16.456+0.002*Z10+0.009*Z11$
LASSO	$-0.000034*Z370+0.000913*Z460-0.00044*Z21+1.400393*Z31+0.007377*Z41+0.000279*Z371+0.0000622*Z451+57.6$

4.2.2.2.2 Weather based prediction CAFAD of potato late blight under normal planting for Kalyani

Models for predicting crop age at first appearance of disease for Kalyani location under normal planting were developed using long term CAFAD data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.18). Models developed had R² ranging between 0.763** (LASSO, LASSO-SVM, SMLR-SVM and SMLR) to 0.992*** (SVM). Calibration and validation of the models developed using different techniques to predict crop age at first appearance of disease (CAFAD) for Kalyani location under normal planting are shown in Table 4.28. RMSE for calibration ranged from 0.784 (SVM) to 6.706 (LASSO). Value of RMSE ascended as 0.784 (SVM), < 3.718 (SMLR), < 3.908 (LASSO-SVM, SMLR-SVM) and < 6.706 (LASSO). Mean absolute percentage error for calibration ranged between 1.271 % (SVM) to 8.688 % (LASSO). Value of MAPE ascended as 1.271 % (SVM), < 3.226 %

(LASSO-SVM), < 3.226% (SMLR-SVM), < 3.679 % (SMLR) and < 8.688 % (LASSO). Value of nRMSE for calibration ranged between 0.013 (SVM) to 0.107 (LASSO). Value of nRMSE descended as 0.107 (LASSO), < 0.062 (LASSO-SVM), < 0.062 (SMLR-SVM), < 0.059 (SMLR), and < 0.013 (SVM).

RMSE for validation ranged between 3.715 (SMLR) to 6.520 (SVM). Value of RMSE ascended as 3.715 (SMLR), < 4.731 (LASSO-SVM), < 4.731 (SMLR-SVM), < 6.136 (LASSO) and < 6.520 (SVM) (Table 4.28). Value of nRMSE for validation ranged between 0.069 (SMLR) to 0.120 (SVM). Value of nRMSE ascended as 0.069 (SMLR), < 0.087 (LASSO-SVM, SMLR-SVM) < 0.113 (LASSO) and < 0.120 (SVM). MAPE for validation ranged between 4.191 % (LASSO-SVM) to 9.990 % (LASSO). Value of MAPE ascended as 4.191 % (LASSO-SVM), < 4.191 % (SMLR-SVM), < 5.180 % (SMLR) < 8.461 % (SVM), and < 9.990 % (LASSO). Among the models developed to predict crop age at first appearance of disease (CAFAD) for Kalyani location under normal planting, the model developed by SMLR technique performed the best followed by LASSO-SVM, SMLR-SVM, LASSO and SVM.

The most important weather indices identified for prediction of crop age at first appearance of disease (CAFAD) for Kalyani location under normal planting by SMLR model was Z10 (sum of daily maximum temperature), while important weather indices identified from LASSO model was Z10 (sum of daily maximum temperature) (Table 4.29).

Table 4.28 Weather based prediction of crop age at first appearance of disease (CAFAD) under normal planting conditions for Kalyani

S N	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ² (%)	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.992***	0.784	0.013	1.271	6.520	0.120	8.461
2	LASSO	0.763**	6.706	0.107	8.688	6.136	0.113	9.990
3	SMLR	0.763**	3.718	0.059	3.679	3.715	0.069	5.180
4	LASSO-SVM	0.763**	3.908	0.062	3.226	4.731	0.087	4.191
5	SMLR-SVM	0.763**	3.908	0.062	3.226	4.731	0.087	4.191

Table 4.29 Equation for prediction of crop age at first appearance of disease (CAFAD) for normal planting for Kalyani location

Techniques used for developing model	Equation
SMLR	$5.01+0.003*Z10$
LASSO	$0.000344916762371241*Z10+ 57.98$

4.2.2.2.3 Weather based prediction CAFAD of potato late blight under normal planting for Kalyani

Models for predicting crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location under late planting conditions were developed using long term CAFAD data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.19). Models developed had the value of R^2 ranging between 0.809** (SMLR and SMLR-SVM) to 0.993*** (SVM). Value of R^2 varied as 0.809** (SMLR and SMLR-SVM), < 0.910*** (LASSO), < 0.958*** (LASSO-SVM) and < 0.993*** (SVM). Calibration and validation of the models developed to predicting crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location under late planting conditions is shown in Table 4.30. RMSE for calibration ranged between 0.851 (SVM) to 4.070 (SMLR-SVM). Value of RMSE ascended as, 0.851 (SVM), < 1.876 (LASSO-SVM), < 2.909 (LASSO), < 3.852 (SMLR) and < 4.070 (SMLR-SVM). Mean absolute percentage error for calibration ranged between 1.535 % (SVM) to 6.475 (SMLR). Value of MAPE ascended as 1.535% (SVM), < 2.444% (LASSO-SVM), < 4.577% (LASSO), < 5.659% (SMLR-SVM), < 6.475% (SMLR). Value of nRMSE for calibration ranged between 0.015 (SVM), to 0.073 (SMLR-SVM). Value of nRMSE ascended as 0.015 (SVM), < 0.034 (LASSO-SVM), < 0.052 (LASSO), < 0.069 (SMLR), < 0.073 (SMLR-SVM).

RMSE for validation ranged between 2.955 (SVM) to 3.747 (LASSO-SVM). Value of RMSE ascended as 2.955 (SVM), < 3.180 (LASSO), < 3.215 (SMLR-SVM), < 3.564 (SMLR) and < 3.747 (LASSO-SVM) (Table 4.30). Value of nRMSE for validation ranged between 0.060 (SVM) to 0.076 (LASSO-SVM). Value of nRMSE ascended as 0.060 (SVM), < 0.064 (LASSO), < 0.065 (SMLR-SVM), < 0.072 (SMLR), < 0.076 (LASSO-SVM). MAPE for validation ranged between 5.336% (LASSO) to 7.312% (LASSO-SVM). Value of MAPE ascended as 5.336 % (LASSO), < 5.637 % (SVM), < 5.777% (SMLR-SVM), < 6.277 % (SMLR) and < 7.312% (LASSO-SVM). Among the models developed to predict the crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location under late planting conditions, the model developed by SVM technique performed the best followed by LASSO, SMLR-SVM, SMLR and LASSO-SVM.

The most important weather indices identified for prediction of disease severity by SMLR model (Table 4.31) was Z21 (sum of weighted minimum temperature). While the important weather indices predicted by LASSO were Z70 (sum of daily solar radiation), Z370 (sum of daily rainfall* daily solar radiation), Z21 (sum of weighted minimum temperature), Z41 (sum of weighted morning relative humidity), Z71 (sum of weighted solar radiation) and Z371 (sum of weighted rainfall*weighted solar radiation) (Table 4.31).

Table 4.30 Weather-based prediction of crop age at first appearance of disease (CAFAD) for late planting by different models for Kalyani

S No	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.993***	0.851	0.015	1.535	2.955	0.060	5.637
2	LASSO	0.910***	2.909	0.052	4.577	3.180	0.064	5.336
3	SMLR	0.809**	3.852	0.069	6.475	3.564	0.072	6.277
4	LASSO-SVM	0.958***	1.876	0.034	2.444	3.747	0.076	7.312
5	SMLR-SVM	0.809**	4.070	0.073	5.659	3.215	0.065	5.777

Table 4.31 Equation for prediction of crop age at first appearance of disease (CAFAD) for late planting for Kalyani location

Techniques used for developing model	Equation
SMLR	$12.179+0.003*Z21$
LASSO	$0.0000716*Z70-0.0000157*Z370+0.001512*Z21-0.00062*Z41+0.000139*Z71+0.00000112*Z371+ 17.37$

4.2.2.2.4 Weather based prediction CAFAD of potato late blight for all plantings (pooled data) for Kalyani

Models for predicting the crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location for all plantings (pooled data) were developed using long term CAFAD data along with daily weather data during potato crop growth period under early, normal and late

planting from 2006 to 2020 (Fig 4.20). Models developed had the R^2 between 0.742*** (SMLR) to 0.970*** (SVM). Value of R^2 varied as 0.742*** (SMLR), < 0.859*** (SMLR-SVM), < 0.919*** (LASSO) and < LASSO-SVM and < 0.970*** (SVM). Calibration and validation of the models developed using different techniques for all plantings is shown in Table 4.32. RMSE for calibration ranged between 1.598 (SVM) to 82.234 (SMLR). Value of RMSE ascended as, 1.598 (SVM), < 2.669 (LASSO), < 2.689 (LASSO-SVM), < 3.656 (SMLR-SVM) and < 82.234 (SMLR). Mean absolute percentage error for calibration ranged between 2.218 % (SVM) and 79.716 (SMLR). Value of MAPE ascended as 2.218% (SVM), < 3.663% (LASSO-SVM), < 3.783% (LASSO), < 4.176% (SMLR-SVM) and < 79.716% (SMLR). Value of nRMSE for calibration ranged between 0.026 (SVM) to 1.008 (SMLR). Value of nRMSE ascended as 0.026 (SVM), < 0.043 (LASSO), < 0.043 (LASSO-SVM), < 0.059 (SMLR-SVM), and < 1.008 (SMLR).

RMSE for validation ranged between 4.473 (SVM) to 60.856 (SMLR). Value of RMSE ascended as 4.473 (SVM), < 4.710 (SMLR-SVM), < 5.585 (LASSO-SVM), < 22.820 (LASSO) and < 60.856 (SMLR) (Table 4.32). Value of nRMSE for validation ranged between 0.079 (SVM) to 1.077 (SMLR). Value of nRMSE ascended as 0.079 (SVM), < 0.083 (SMLR-SVM), < 0.099 (LASSO-SVM), < 0.284 (LASSO) and < 1.077 (SMLR). MAPE for validation ranged between 5.425% (SMLR-SVM) to 94.838% (SMLR). Value of MAPE ascended as 5.425 % (SMLR-SVM), < 6.580 % (SVM), < 9.136% (LASSO-SVM), < 17.162 % (LASSO) and < 94.838 % (SMLR). Among the models developed to predict the crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location for all plantings (pooled data), the model developed by SVM technique performed the best followed by LASSO-SVM and SMLR-SVM. nRMSE value of LASSO and SMLR were higher than the range.

The most important weather indices identified to predict the crop age at first appearance of disease (CAFAD) for potato late blight at Kalyani location for all plantings (pooled data) by SMLR model (Table 4.33) were Z10 (sum of daily maximum temperature), Z40 (Z41 (sum of daily morning relative humidity) and Z370 (sum of daily rainfall* solar radiation). While the important weather indices identified by LASSO model were Z10 (sum of daily maximum temperature), Z360 (sum of daily rainfall* wind speed), Z370 (sum of daily rainfall* solar radiation), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z61 (sum of weighted wind speed), Z161 (sum of weighted maximum temperature*weighted wind speed), Z261 (sum of weighted minimum temperature*weighted wind speed) and Z351 (sum of weighted rainfall*weighted evening relative humidity) (Table 4.33).

Table 4.32 Weather-based prediction of crop age at first appearance of disease (CAFAD) for all plantings (pooled together) by different models for Kalyani

S No	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.970***	1.598	0.026	2.218	4.473	0.079	6.580
2	LASSO	0.919***	2.669	0.043	3.783	22.820	0.284	17.16
3	SMLR	0.742***	82.234	1.008	79.716	60.856	1.077	94.84
4	LASSO-SVM	0.919***	2.689	0.043	3.663	5.585	0.099	9.136
5	SMLR-SVM	0.859***	3.656	0.059	4.176	4.710	0.083	5.425

Table 4.33 Equation for prediction of crop age at first appearance of disease (CAFAD) of all plantings (pooled data) for Kalyani location

Techniques used for developing model	Equation
SMLR	$-315.911+0.009*Z10-0.00005422*Z370+0.039*Z40$
LASSO	$0.00205*Z10+0.0488*Z360-0.0000374*Z370+0.000237*Z21+0.16211*Z31+0.0976*Z61+0.0000744*Z161+2.54E-18*Z261+0.00349*Z351+16.63$

4.2.3 Weather based prediction of potato late blight crop age at maximum disease severity (CAMDS) in two different locations under different planting

4.2.3.1 Weather based prediction CAMDS of potato late blight in Srinagar

4.2.3.1.1 Weather based prediction CAMDS of potato late blight under early planting for Srinagar

Models for predicting crop age at maximum disease severity (CAMDS) for Srinagar location under early planting conditions were developed using long term CAMDS data along with daily weather data during crop growth period from 2006 to 2020 (Fig 4.21). Models developed had the R² value ranging between 0.969*** (SMLR and SMLR-SVM) to 0.992*** (SVM). Value of R² descended as 0.992*** (SVM), > 0.990*** (SMLR-SVM), > 0.982*** (LASSO-SVM), > 0.981*** (LASSO) and > 0.969** (SMLR). Calibration and validation of the models developed using different techniques to predict crop age at maximum disease severity (CAMDS) for Srinagar location under early planting conditions is shown in Table 4.34. RMSE for calibration ranged between 1.141 (SVM) and 27.895 (SMLR). Value of RMSE ascended as 1.141 (SVM), < 1.636 (LASSO-SVM), < 1.772 (LASSO), < 2.056 (SMLR) and < 27.895 (SMLR-SVM).

Mean absolute percentage error for calibration ranged between 0.983 % (LASSO) and 25.870 % (SMLR-SVM). Value of MAPE ascended as 0.983 % (LASSO), < 1.253 % (SMLR), < 1.256 % (LASSO-SVM), < 10.235 % (SVM) and < 25.870 % (SMLR-SVM). Value of nRMSE for calibration ranged between 0.015 (LASSO-SVM) to 0.256 (SMLR-SVM). Value of nRMSE ascended as 0.015 (LASSO-SVM), < 0.016 (LASSO), < 0.019 (SMLR), < 0.047 (SVM) and < 0.256 (SMLR-SVM).

RMSE for validation ranged between 24.121 (LASSO-SVM) and 44.578 (SMLR-SVM). Value of RMSE ascended as 24.121 (LASSO-SVM), < 24.320 (LASSO), < 35.000 (SMLR), < 40.401 (SVM), and < 44.578 (SMLR-SVM) (Table 4.34). Value of nRMSE for validation ranged between 0.211 (LASSO-SVM) and 0.390 (SMLR-SVM). Value of nRMSE ascended as 0.211 (LASSO-SVM), 0.213 (LASSO), < 0.306 (SMLR), < 0.390 (SMLR-SVM) and < 0.353 (SVM). MAPE for validation ranged between 12.039 % (LASSO-SVM) and 28.495 % (SMLR-SVM). Value of MAPE ascended as 12.039 % (LASSO-SVM), < 12.045 % (LASSO), < 17.742 % (SMLR), < 20.919 % (SVM) and < 28.495% (SMLR-SVM). Among the models developed to predict crop age at maximum disease severity (CAMDS) for Srinagar location under early planting conditions, none of the models performed well however, model developed by LASSO-SVM technique had lowest nRMSE value (0.21).

The most important weather indices identified for prediction of crop age at maximum disease severity (CAMDS) for Srinagar location under early planting conditions by SMLR model (Table 4.35) was Z21 (sum of weighted minimum temperature). While the important weather indices identified by LASSO were Z360 (sum of daily rainfall*wind speed), Z11 (sum of weighted maximum temperature), Z21 (sum of weighted minimum temperature), Z41 (sum of weighted morning relative humidity), Z361 (sum of weighted rainfall*weighted wind speed)

Table 4.34 Weather based prediction of crop age at maximum disease severity (CAMDS) for early planting by different models for Srinagar

S N	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.992***	1.141	0.047	10.235	40.401	0.353	20.919
2	LASSO	0.981***	1.772	0.016	0.983	24.320	0.213	12.045
3	SMLR	0.969***	2.056	0.019	1.253	35.000	0.306	17.742
4	LASSO-SVM	0.982***	1.636	0.015	1.256	24.121	0.211	12.039
5	SMLR-SVM	0.990***	27.895	0.256	25.870	44.578	0.390	28.495

Table 4.35 Equation for prediction of crop age at maximum disease severity (CAMDS) for early planting for Srinagar location

Techniques used for developing model	Equation
SMLR	$37.25952 - 0.006 * Z_{21}$
LASSO	$-0.00214 * Z_{360} + 0.003353 * Z_{11} - 0.00454 * Z_{21} + 0.002273 * Z_{41} + 3.63E-05 * Z_{361} + 38.4405643$

4.2.3.1.2 Weather based prediction CAMDS of potato late blight under normal planting for Srinagar

Models for predicting crop age at maximum disease severity (CAMDS) for potato late blight at Srinagar location under normal planting conditions were developed using long term CAMDS data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.22). Models developed had the R^2 ranging between 0.629* (SMLR, LASSO, LASSO-SVM) to 0.995*** (SVM). Value of R^2 ascended as 0.629* (SMLR, LASSO-SVM and SMLR), < 0.991*** (SMLR-SVM), and < 0.995*** (SVM). RMSE for calibration ranged between 1.347 (SVM) and 9.583 (SMLR-SVM). Value of RMSE ascended as 1.347 (SVM), < 1.637 (LASSO), < 1.650 (LASSO-SVM), < 5.286 (SMLR-SVM) and < 9.583 (SMLR) (Table 4.36). Similarly, mean absolute percentage error for calibration ranged between 16.638 % (SVM) and 70.890 % (SMLR). Value of MAPE ascended as 16.638 % (SVM), < 19.129 % (LASSO), < 19.254 % (LASSO-SVM), < 41.917 % (SMLR-SVM) and < 70.890 % (SMLR). Value of nRMSE for calibration ranged between 0.050 (SVM) to 0.359 (SMLR). Value of nRMSE ascended as 0.050 SVM, < 0.061 (LASSO), < 0.062 (LASSO-SVM), < 0.198 (SMLR-SVM) and < 0.359 (SMLR).

RMSE for validation ranged between 5.530 (SVM) to 12.161 (SMLR). Value of RMSE ascended as 5.530 (SVM), < 5.332 (SMLR-SVM), < 5.337 (LASSO-SVM), < 5.941 (LASSO) and < 12.161 (SMLR) (Table 4.36). Value of nRMSE for validation ranged between 0.174 (SMLR-SVM) and LASSO-SVM and 0.397 (SMLR). Value of nRMSE ascended as 0.174 (LASSO-SVM and SMLR-SVM), < 0.180 (SVM), < 0.194 (LASSO) and < 0.397 (SMLR). MAPE for validation ranged between 14.291 % (SVM) and 32.154 % (SMLR). Value of MAPE ascended as 14.291 % (SVM), 15.201 % (SMLR-SVM), 15.940 % (LASSO-SVM), 16.880 % (LASSO), 32.154 % (SMLR). Among the models developed to predict crop age at maximum disease severity (CAMDS) for potato late blight at Srinagar location under normal planting conditions, none of the models performed well however, model developed by LASSO-SVM and SMLR-SVM technique has lowest nRMSE value (0.174).

The most important weather indices identified by SMLR model was Z21 (sum of weighted minimum temperature), while important weather indices identified by LASSO model was Z21 (sum of weighted minimum temperature) (Table 4.37).

Table 4.36 Weather based prediction of crop age at maximum disease severity (CAMDS) under normal planting by different models for Srinagar

S N	Model	Model accuracy parameters during calibration			Model accuracy parameters during validation			
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.995***	1.347	0.050	16.638	5.530	0.180	14.291
2	LASSO	0.629*	1.637	0.061	19.129	5.941	0.194	16.880
3	SMLR	0.629*	9.583	0.359	70.890	12.161	0.397	32.154
4	LASSO-SVM	0.629*	1.650	0.062	19.254	5.337	0.174	15.940
5	SMLR-SVM	0.991***	5.286	0.198	41.917	5.332	0.174	15.201

Table 4.37 Equation for prediction of crop age at maximum disease severity (CAMDS) for normal planting for Srinagar location

Techniques used for developing model	Equation
SMLR	$-0.92172 - 0.01 * Z21$
LASSO	$-0.00357 * Z21 + 70.97964744$

4.2.3.1.3 Weather based prediction CAMDS of potato late blight under late planting for Srinagar

Models for predicting crop age at maximum disease severity (CAMDS) at Srinagar location under normal planting were developed using long term CAMDS data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.23). Models developed had the R² ranging between 0.919*** (LASSO-SVM) to 0.943*** (LASSO). Value of R squared varied as 0.929*** (SMLR) < 0.926*** (SMLR-SVM), < 0.943*** (LASSO), < 0.919*** (LASSO-SVM) and < 0.927*** (SVM). Calibration and validation of the models developed to predict crop age at maximum disease severity (CAMDS) at Srinagar location under normal planting using different techniques is shown in Table 4.38. RMSE for calibration ranged between 1.682 (SVM) to 30.285 (SMLR-SVM). Value of RMSE ascended as, 1.682 (SVM), < 4.712 (LASSO), < 5.181 (SMLR), < 5.373 (LASSO-SVM) and < 30.285 (SMLR-SVM). Mean absolute percentage error for calibration varied as 3.439 (LASSO), < 3.777 (SMLR), < 4.256 (LASSO-

SVM) < 15.212 (SVM), and < 27.446 (SMLR-SVM). Value of nRMSE for calibration ranged between 0.042 (LASSO) to 1.544 (SVM). Value of nRMSE ascended as 0.042 (LASSO), < 0.047 (SMLR), < 0.048 (LASSO-SVM), < 0.273 (SMLR-SVM), and < 1.544 (SVM).

RMSE for validation ranged between 3.439 (LASSO) to 50.345 (SMLR-SVM). Value of RMSE ascended as 3.576 (LASSO), < 14.389 (LASSO-SVM), < 19.297 (SVM), < 27.598 (SMLR), and < 50.345 (SMLR-SVM) (Table 4.38). Value of nRMSE for validation ranged between 0.033 (LASSO) to 0.180 (SVM). Value of nRMSE ascended as 0.033 (LASSO), < 0.134 (LASSO-SVM), < 0.180 (SVM) < 0.257 (SMLR) and < 0.470 (SMLR-SVM). MAPE for validation ranged between 2.937 % (LASSO) to 38.035 (SMLR-SVM). Value of MAPE ascended as 2.937 % (LASSO), < 8.363 % (LASSO-SVM), < 10.682% (SVM), < 13.450% (SMLR), and < 38.035 % (SMLR-SVM). Among the models developed to predict crop age at maximum disease severity (CAMDS) for potato late blight at Srinagar location under normal planting, the model developed by LASSO technique performed the best while other models had higher nRMSE values.

The most important weather indices identified for prediction of crop age at maximum disease severity (CAMDS) for potato late blight at Srinagar location under normal planting (Table 4.39), by SMLR model were Z21 (sum of weighted minimum temperature), Z61 (sum of weighted wind speed). Similarly, important weather indices identified by LASSO were Z11 (sum of weighted maximum temperature), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z41 (sum of weighted morning relative humidity), and Z61 (sum of weighted wind speed).

Table 4.38 Weather based prediction of crop age at maximum disease severity (CAMDS) for late planting by different models for Srinagar

S N	Model	Model accuracy parameters during calibration			Model accuracy parameters during validation			
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.927***	1.682	1.544	15.212	19.297	0.180	10.682
2	LASSO	0.943***	4.712	0.042	3.439	3.576	0.033	2.937
3	SMLR	0.929***	5.181	0.047	3.777	27.598	0.257	13.450
4	LASSO-SVM	0.919***	5.373	0.048	4.256	14.389	0.134	8.363
5	SMLR-SVM	0.926***	30.285	0.273	27.446	50.345	0.470	38.035

Table 4.39 Equation for prediction of crop age at maximum disease severity (CAMDS) for late planting for Srinagar location

Techniques used for developing model	Equation
SMLR	$10.61197 - 0.008 * Z_{21} + 0.682 * Z_{61}$
LASSO	$-0.00218 * Z_{11} + 0.00543 * Z_{21} + 0.003473 * Z_{31} + 0.004278 * Z_{41} + 0.400915 * Z_{61} + 24.51555136$

4.2.3.1.4 Weather based prediction CAMDS of potato late blight for all plantings (pooled data) for Srinagar

Models for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Srinagar location for all different plantings pooled together were developed using long term CAMDS data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.24). Models developed had R^2 ranging between 0.694*** (SMLR) to 0.909*** (SVM). Value of R^2 descended as 0.909*** (SVM), < 0.902*** (LASSO), < 0.892*** (LASSO-SVM), < 0.929*** (SMLR-SVM) and < 0.694*** (SMLR). Calibration and validation of the models developed to predict crop age at maximum disease severity (CAMDS) for potato late blight, at Srinagar location for all different plantings pooled together using different techniques for all plantings is shown in Table 4.40. RMSE for calibration ranged between 4.833 (SVM) and 28.995 (SMLR-SVM). Value of RMSE ascended as 4.833 (SVM), < 5.044 (LASSO), < 5.435 (LASSO-SVM), < 8.864 (SMLR) and < 28.995 (SMLR-SVM). Mean absolute percentage error for calibration ranged between 2.874% (LASSO-SVM) and 79.448 % (SVM). Value of MAPE ascended as 2.874 % (LASSO-SVM), < 2.992% (LASSO), < 6.147% (SMLR), < 26.532 % (SMLR-SVM), and < 79.448% (SVM). nRMSE for calibration ranged between 0.044 (SVM) and 0.265 (SMLR-SVM). Value of nRMSE ascended as 0.044 (SVM), < 0.046 (LASSO), < 0.050 (LASSO-SVM), < 0.081 (SMLR) and < 0.265 (SMLR-SVM).

RMSE for validation ranged between 29.237 (SMLR) and 56.533 (SVM). Value of RMSE ascended as 29.237 (SMLR), < 37.142 (LASSO), < 38.611 (SMLR-SVM), < 46.606 (LASSO-SVM) and 56.533 (SVM) (Table 4.40). Value of nRMSE for validation ranged between 0.270 (SMLR) and 0.522 (SVM). Value of nRMSE ascended as 0.270 (SMLR), < 0.343 (LASSO), < 0.356 (SMLR-SVM), < 0.430 (LASSO-SVM) and < 0.522 (SVM). MAPE for validation ranged between 15.019 % (SMLR) and 30.127 % (SMLR-SVM). Value of MAPE ascended as 15.019% (SMLR), < 16.949 % (LASSO) < 20.795 % (LASSO-SVM), < 25.262 % (SVM) and < 30.127 % (SMLR-SVM). Among the models developed predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Srinagar location for all different plantings

pooled together, none of the models performed well however model developed by SMLR technique had lowest nRMSE value (0.270).

The most important weather indices identified for prediction of crop age at maximum disease severity (CAMDS) for potato late blight, at Srinagar location for all different plantings pooled together (Table 4.41), by SMLR model were Z21 (sum of weighted minimum temperature), Z61 (sum of weighted wind speed), Z671 (sum of weighted wind speed * weighted solar radiation). While important weather indices identified by LASSO were Z10 (sum of daily solar radiation), Z240 (sum of daily minimum temperature* morning relative humidity), Z270 (sum of daily minimum temperature* solar radiation), Z670 (sum of daily wind speed*solar radiation), Z21 (sum of weighted minimum temperature), Z31 (sum of weighted rainfall), Z41 (sum of weighted morning relative humidity), Z61 (sum of weighted wind speed), Z71 (sum of weighted solar radiation), Z171 (sum of weighted maximum temperature*weighted solar radiation), Z451 (sum of weighted morning relative humidity*weighted evening relative humidity), Z671 (sum of weighted wind speed* weighted solar radiation).

Table 4.40 weather-based prediction of crop age at maximum disease severity (CAMDS) for all plantings (pooled data) by different models for Srinagar

S N	Model	Model accuracy parameters during calibration			Model accuracy parameters during validation			
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.909***	4.833	0.044	79.448	56.533	0.522	25.262
2	LASSO	0.902***	5.044	0.046	2.992	37.142	0.343	16.949
3	SMLR	0.694***	8.864	0.081	6.147	29.237	0.270	15.019
4	LASSO-SVM	0.892***	5.435	0.050	2.874	46.606	0.430	20.795
5	SMLR-SVM	0.929***	28.995	0.265	26.532	38.611	0.356	30.127

Table 4.41 Equation for prediction of crop age at maximum disease severity (CAMDS) for all plantings for Srinagar location

Techniques used for developing model	Equation
SMLR	$28.31255 - 0.007 * Z_{21} + 6.107E-005 * Z_{671} + 0.489 * Z_{61}$
LASSO	$-2.54E-05 * Z_{70} - 2.59E-05 * Z_{240} - 2.47E-09 * Z_{270} - 1.08E-05 * Z_{670} - 0.00326 * Z_{21} + 0.05177 * Z_{31} + 0.011025 * Z_{41} + 0.078766 * Z_{61} - 0.00021 * Z_{71} + 2.17E-08 * Z_{171} - 3.18E-05 * Z_{451} + 3.20E-05 * Z_{671} + 191.3735582$

4.2.3.2 Weather based prediction CAMDS of potato late blight in Kalyani

4.2.3.2.1 Weather based prediction CAMDS of potato late blight under early planting for Kalyani

Models for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under early planting condition were developed using long term CAMDS data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.25). Models developed had R^2 ranging between 0.003^{ns} (SMLR) to 0.999^{***} (LASSO). Value of R^2 varied as 0.003^{ns} (SMLR), < 0.996^{***} (SMLR-SVM), < 0.996^{***} (SVM), < 0.996^{***} (LASSO-SVM) and 0.999^{***} (LASSO). Calibration and validation of the models developed for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under early planting condition using different techniques is shown in Table 4.42. RMSE for calibration ranged between 0.168 (LASSO) to 0.920 (SMLR). Value of RMSE ascended as 0.168 (LASSO), < 0.622 (SMLR-SVM), < 0.641 (LASSO-SVM), < 0.641 (SVM) and < 0.920 (SMLR). Mean absolute percentage error for calibration ranged between 0.115 % (LASSO) to 0.761 % (SMLR). Value of MAPE ascended as 0.115 % (LASSO), < 0.593 (SMLR-SVM), < 0.616% (LASSO-SVM), < 0.638% (SVM), < 0.761% (SMLR). Value of nRMSE for calibration ranged between 0.002 (LASSO) to 0.010 (SMLR). Value of nRMSE ascended as 0.002 (LASSO), < 0.006 (SMLR-SVM), < 0.007 (SVM, LASSO-SVM) and 0.010 (SMLR).

RMSE for validation ranged between 0.378 (SMLR) to 1.375 (SVM). Value of RMSE ascended as 0.378 (SMLR), < 0.434 (LASSO) < 0.922 (LASSO-SVM), 1.234 (SMLR-SVM), and < 1.375 (SVM) (Table 4.42). Value of nRMSE for validation ranged between 0.010 (SMLR-SVM) to 0.015 (SVM). Value of nRMSE ascended as 0.005 (SMLR, LASSO), < 0.010 (LASSO-SVM), < 0.013 (SMLR-SVM), < 0.015 (SVM). MAPE for validation ranged between 0.388% (LASSO) to 1.255% (SMLR-SVM). Value of MAPE ascended as 0.388 % (LASSO), < 0.415 % (SMLR), < 0.684% (LASSO-SVM), < 1.079% (SVM) and < 1.255% (SMLR-SVM). Among the models developed for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under early planting condition, the model developed by LASSO technique performed the best followed by LASSO-SVM, SMLR-SVM and SVM.

The most important weather indices identified for prediction of crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under early planting condition (Table 4.43) by SMLR model were Z10 (sum of daily maximum temperature), Z360 (sum of daily rainfall*wind speed), Z71 (sum of weighted solar radiation), Z121 ((sum of weighted

maximum temperature* weighted minimum temperature), Z341 (sum of weighted rainfall*weighted morning relative humidity), Z471 (sum of weighted morning relative humidity*weighted solar radiation). While the important weather indices identified by LASSO model were Z10 (sum of daily maximum temperature), Z70 (sum of daily solar radiation), Z270 (sum of daily minimum temperature* solar radiation), Z470 (sum of daily morning relative humidity*solar radiation), Z471 (sum of weighted morning relative humidity*weighted solar radiation).

Table 4.42 Weather based prediction of crop age at maximum disease severity (CAMDS) under early planting conditions by different models for Kalyani

S N	Model	Model accuracy parameters during calibration			Model accuracy parameters during validation			
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.996***	0.641	0.007	0.638	1.375	0.015	1.079
2	LASSO	0.999***	0.168	0.002	0.115	0.434	0.005	0.388
3	SMLR	0.003 ^{ns}	0.920	0.010	0.761	0.378	0.005	0.415
4	LASSO-SVM	0.996***	0.638	0.007	0.616	0.922	0.010	0.684
5	SMLR-SVM	0.996***	0.622	0.006	0.593	1.234	0.013	1.255

Table 4.43 Equation for prediction of crop age at maximum disease severity (CAMDS) for early planting for Kalyani location

Techniques used for developing model	Equation
SMLR	$-1.773+0.004*Z10-0.00003969*Z71 -0.000002511*Z121 - 0.002*Z360-0.00005455*Z341+0.0000001031*Z471$
LASSO	$0.003*Z10+0.00000357*Z70 +0.000000051*Z270+0.000000221*Z470 +0.00000000000000447*Z471+ 0.62$

4.2.3.2.2 Weather based prediction CAMDS of potato late blight under normal planting for Kalyani

Models for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under normal planting condition were developed using long term CAMDS

data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.26). Models developed had the value of R^2 ranging between 0.996*** (SVM) to 0.999*** (LASSO). Value of R^2 varied as 0.999*** (LASSO, SMLR and SMLR-SVM) > 0.997*** (LASSO-SVM) and > 0.996*** (SVM). Calibration and validation of the models developed for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under normal planting condition using different techniques is shown in Table 4.44. RMSE for calibration ranged between 0.310 (LASSO) to 0.949 (SVM). Value of RMSE ascended as 0.310 (LASSO), < 0.734 (LASSO-SVM), < 0.761 (SMLR-SVM), < 0.920 (SMLR) and < 0.949 (SVM). Mean absolute percentage error for calibration ranged between 0.257% (LASSO) to 1.051 % (SVM). Value of MAPE ascended as 0.257 (LASSO), < 0.761% (SMLR), < 0.775% (LASSO-SVM), < 0.791% (SMLR-SVM), and < 1.057 % (SVM). Value of nRMSE for calibration ranged between 0.003 (LASSO) to 0.011 (SVM). Value of nRMSE ascended as, 0.003 (LASSO), < 0.008 (LASSO-SVM), < 0.009 (SMLR-SVM), < 0.010 (SMLR) and < 0.011 (SVM).

RMSE for validation ranged between 0.221 (LASSO) to 4.610 (SVM). Value of RMSE ascended as 0.221(LASSO), < 0.378 (SMLR), < 0.685 (SMLR-SVM) < 1.285 (LASSO-SVM) and < 4.610 (SVM) (Table 4.44). Value of nRMSE for validation ranged between 0.003 (LASSO) to 0.056 (SVM). Value of nRMSE ascended as 0.003 (LASSO), < 0.005 (SMLR), < 0.008 (SMLR-SVM), < 0.016 (LASSO-SVM), < 0.056 (SVM). MAPE for validation ranged between 0.236% (LASSO) to 4.419% (SVM). Value of MAPE ascended as 0.236 % (LASSO), < 0.415 % (SMLR), < 0.727 % (SMLR-SVM), < 1.294% (LASSO-SVM) and < 4.419 % (SVM). Among the models developed for predicting the crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under normal planting condition developed by LASSO technique performed the best followed by SMLR, SMLR-SVM, LASSO-SVM, and SVM.

The most important weather indices identified for prediction of crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under normal planting condition by SMLR model was Z10 (sum of daily maximum temperature) (Table 4.45). While important weather indices identified by LASSO model were Z10 (sum of daily maximum temperature), Z20 (sum of daily minimum temperature), Z70 (sum of daily solar radiation), Z270 (sum of daily minimum temperature* solar radiation), Z470(sum of daily morning relative humidity*solar radiation) and Z471 (sum of weighted morning relative humidity*weighted solar radiation).

Table 4.44 Weather based prediction of crop age at maximum disease severity (CAMDS) for normal planting for Kalyani location

S No	Model	Model accuracy parameters during calibration			Model accuracy parameters during validation			
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.996***	0.949	0.011	1.051	4.610	0.056	4.419
2	LASSO	0.999***	0.310	0.003	0.257	0.221	0.003	0.236
3	SMLR	0.999***	0.920	0.010	0.761	0.378	0.005	0.415
4	LASSO-SVM	0.997***	0.734	0.008	0.775	1.285	0.016	1.294
5	SMLR-SVM	0.999***	0.761	0.009	0.791	0.685	0.008	0.727

Table 4.45 Equation for prediction of crop age at maximum disease severity (CAMDS) for normal planting for Kalyani location

Techniques used for developing model	Equation
SMLR	$-0.557+0.003*Z_{10}$
LASSO	$0.003*Z_{10}+0.0000000414*Z_{20}+0.000000228*Z_{70}+0.000000029*Z_{270}+0.0000000593*Z_{470}+0.000000000000000681*Z_{471}+ 2.7$

4.2.3.2.3 Weather based prediction CAMDS of potato late blight under late planting for Kalyani

Models for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under late planting condition were developed using long term CAMDS data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.27). Models developed had the value of R² ranging between 0.991*** (SMLR-SVM) to 0.999*** (SMLR). Value of R² varied as 0.991*** (SMLR-SVM), < 0.992*** (SVM), < 0.994*** (LASSO-SVM), < 0.999*** (LASSO) and SMLR). Calibration and validation of the models developed to predict the crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under late planting condition using different techniques is shown in Table 4.46. RMSE for calibration ranged between 0.226 (SMLR) to 0.944 (SVM). Value of RMSE ascended as 0.226 (SMLR), < 0.298 (LASSO), < 0.848 (LASSO-SVM), < 0.910 (SMLR-SVM), < 0.944

(SVM). Mean absolute percentage error for calibration ranged between 0.197 % (SMLR) to 1.118 % (SVM). Value of MAPE ascended as 0.197 % (SMLR), < 0.282 % (LASSO), < 0.981 % (LASSO-SVM), < 1.060 (SMLR-SVM) and < 1.118 % (SVM). Value of nRMSE for calibration ranged between 0.003 (SMLR) to 0.012 (SVM). Value of nRMSE ascended as 0.003 (SMLR), < 0.004 (LASSO), < 0.010 (LASSO-SVM), < 0.011 (SMLR-SVM), and < 0.012 (SVM).

RMSE for validation ranged between 0.160 (LASSO) to 2.072 (SVM). Value of RMSE ascended as 0.160 (LASSO), < 0.364 (SMLR-SVM), < 0.467 (SMLR), < 0.859 (LASSO-SVM) and < 2.072 (SVM) (Table 4.46). Value of nRMSE for validation ranged between 0.002 (LASSO) to 0.027 (SVM). Value of nRMSE ascended as 0.002 (LASSO), < 0.005 (SMLR-SVM), < 0.006 (SMLR), < 0.011 (LASSO-SVM), and < 0.027 (SVM). MAPE for validation ranged between 0.177 % (LASSO) to 2.240 % (SVM). Value of MAPE ascended as 0.177 % (LASSO), < 0.464 % (SMLR-SVM), < 0.498 % (SMLR), < 1.019 % (LASSO-SVM), and < 2.240 % (SVM). Among the models developed for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under late planting condition the model developed by LASSO technique performed the best followed by SMLR-SVM, SMLR, LASSO-SVM and SVM based on nRMSE value.

The most important weather indices identified for prediction of crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under late planting condition (Table 4.47) by SMLR model were Z21 (sum of weighted minimum temperature), Z670 (sum of daily wind speed*solar radiation), Z71 (sum of weighted solar radiation), Z121 (sum of weighted maximum temperature* weighted minimum temperature). While the important weather indices identified by LASSO model were Z70 (sum of daily solar radiation), Z170 (sum of daily maximum temperature* solar radiation), Z670 (sum of daily wind speed*solar radiation), Z11 (sum of weighted maximum temperature), Z21 (sum of weighted minimum temperature) and Z671 (sum of weighted wind speed* weighted solar radiation).

Table 4.46 Weather based prediction of crop age at maximum disease severity (CAMDS) for late planting at Kalyani

S N	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation		
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)
1	SVM	0.992***	0.944	0.012	1.118	2.072	0.027	2.240
2	LASSO	0.999***	0.298	0.004	0.282	0.160	0.002	0.177
3	SMLR	0.999***	0.226	0.003	0.197	0.467	0.006	0.498
4	LASSO-SVM	0.994***	0.848	0.010	0.981	0.859	0.011	1.019
5	SMLR-SVM	0.991***	0.910	0.011	1.060	0.364	0.005	0.464

Table 4.47 Equation for prediction of crop age at maximum disease severity (CAMDS) for late planting for Kalyani location

Techniques used for developing model	Equation
SMLR	$3.548 + 0.004 * Z_{21} + 0.000002612 * Z_{670} - 0.00008138 * Z_{71} - 0.0000006072 * Z_{121}$
LASSO	$0.0000000153 * Z_{70} + 0.0000000152 * Z_{170} + 0.00000147 * Z_{670} - 0.00066 * Z_{11} + 0.003672 * Z_{21} + 0.00000000817 * Z_{671} + 5.33$

4.2.3.2.4 Weather based prediction CAMDS of potato late blight for all plantings (pooled data) for Kalyani

Models for predicting crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under all plantings (pooled data) were developed using long term CAMDS data along with daily weather data during potato crop growth period from 2006 to 2020 (Fig 4.28). Models developed had the value of R² ranging between 0.979*** (SMLR and LASSO-SVM) to 0.993*** (SVM). Value of R² varied as 0.979*** (SMLR, LASSO-SVM and SMLR-SVM), < 0.980*** (SMLR) and < 0.993*** (SVM). Calibration and validation of the models developed to predict the crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under all plantings (pooled data) using different techniques is shown in Table 4.48. RMSE for calibration ranged between 0.924 (SVM) to 3.211 (LASSO). Value of RMSE ascended as, 0.924 (SVM), < 1.609 (LASSO-SVM), < 1.611 (SMLR-SVM), < 1.682 (SMLR) and < 3.211 (LASSO). Mean absolute percentage error for calibration ranged between

0.873 % (LASSO-SVM) to 3.231% (LASSO). Value of MAPE ascended as 0.873% (LASSO-SVM), < 0.972% (SVM), < 1.052 (SMLR-SVM), < 1.384% (SMLR) and < 3.231% (LASSO). Value of nRMSE for calibration ranged between 0.010 (SVM) to 0.036 (LASSO). Value of nRMSE ascended as 0.010 (SVM), < 0.018 (LASSO-SVM, SMLR-SVM), < 0.019 (SMLR) and < 0.036 (LASSO).

RMSE for validation ranged between 0.816 (SMLR-SVM) to 4.762 (SVM). Value of RMSE ascended as 0.816 (SMLR-SVM), < 0.912 (LASSO-SVM), < 1.252 (SMLR), < 2.655 (LASSO) and < 4.762 (SVM) (Table 4.48). Value of nRMSE for validation ranged between 0.010 (SMLR-SVM) to 0.057 (SVM). Value of nRMSE ascended as 0.010 (SMLR-SVM), < 0.011 (LASSO-SVM), < 0.015 (SMLR), < 0.032 (LASSO) and < 0.057 (SVM). MAPE for validation ranged between 0.854% (LASSO-SVM) to 4.942% (SVM). Value of MAPE ascended as 0.854 % (LASSO-SVM), < 0.865 % (SMLR-SVM), < 1.181% (SMLR), < 2.610% (LASSO) and < 4.942 % (SVM). Among the models developed for predicting the crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under all plantings (pooled data), the model developed by SMLR-SVM technique performed the best followed by LASSO-SVM, SMLR, LASSO and SVM.

The most important weather indices identified for prediction of crop age at maximum disease severity (CAMDS) for potato late blight, at Kalyani location under all plantings (pooled data) (Table 4.49), by SMLR model were Z10 (sum of daily maximum temperature) and Z360 (sum of daily rainfall*wind speed). While the important weather indices identified by LASSO model were Z10 (sum of daily maximum temperature), Z270 (sum of daily minimum temperature* solar radiation), Z271 (sum of weighted minimum temperature*weighted solar radiation).

Table 4.48 Weather-based prediction of crop age at maximum disease severity (CAMDS) for all plantings (pooled together) by different models for Kalyani

S No	Model	Model accuracy parameters during calibration				Model accuracy parameters during validation			
		R ²	RMSE (DAP)	nRMSE	MAPE (%)	RMSE (DAP)	nRMSE	MAPE (%)	
1	SVM	0.993***	0.924	0.010	0.972	4.762	0.057	4.942	
2	LASSO	0.979***	3.211	0.036	3.231	2.655	0.032	2.610	
3	SMLR	0.980***	1.682	0.019	1.384	1.252	0.015	1.181	
4	LASSO-SVM	0.979***	1.609	0.018	0.873	0.912	0.011	0.854	
5	SMLR-SVM	0.979***	1.611	0.018	1.052	0.816	0.010	0.865	

Table 4.49 Equation for prediction of crop age at maximum disease severity (CAMDS) for all plantings (pooled data) for Kalyani location

Techniques used for developing model	Equation
SMLR	$2.644+0.003*Z10+0.012*Z360$
LASSO	$0.002*Z10+0.0000000381*Z270+0.0000000489*Z271+ 24.19$

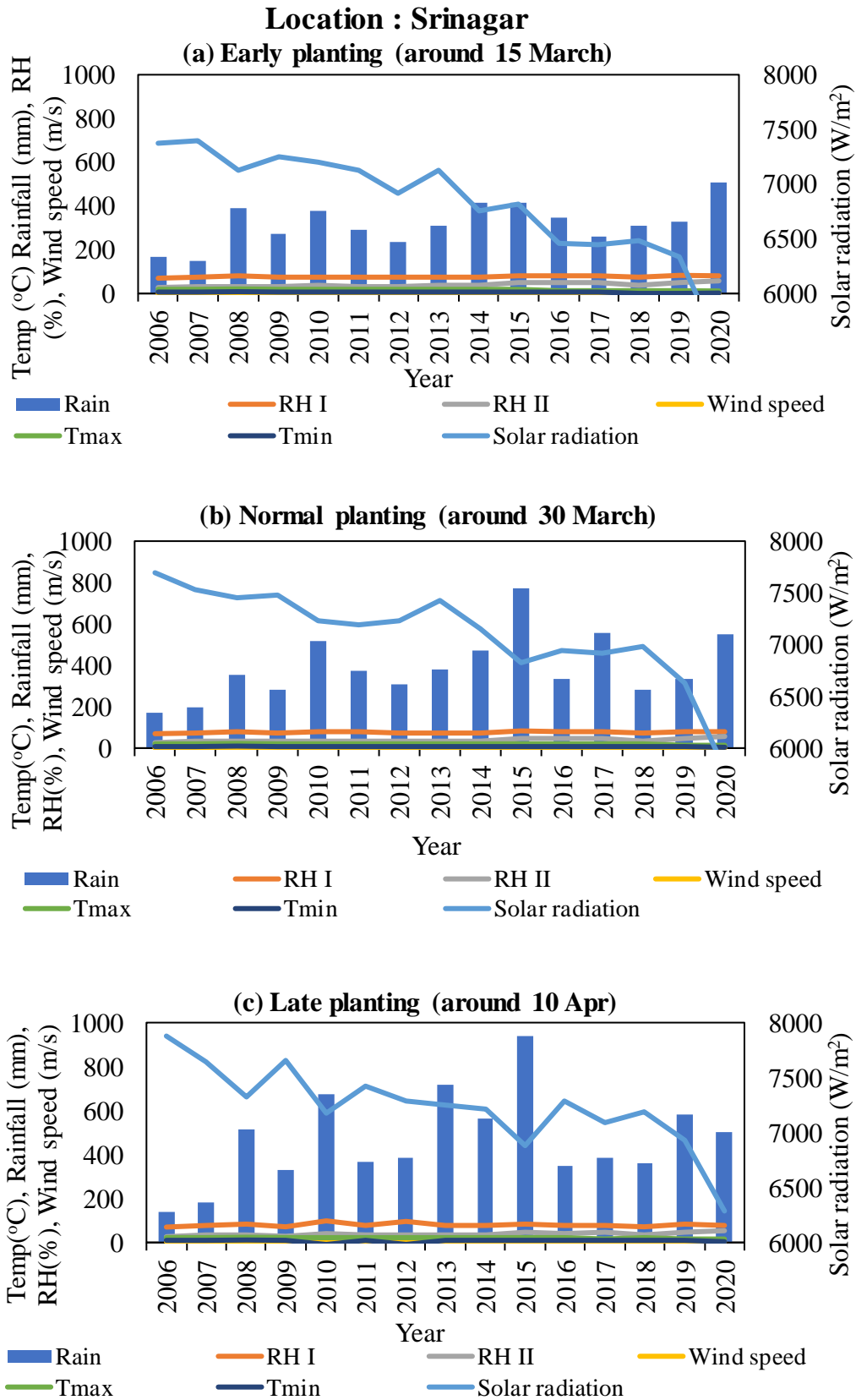


Fig 4.1 Variations in weather parameters with year for different plantings (a) Early, (b) Normal and (c) Late, in Srinagar

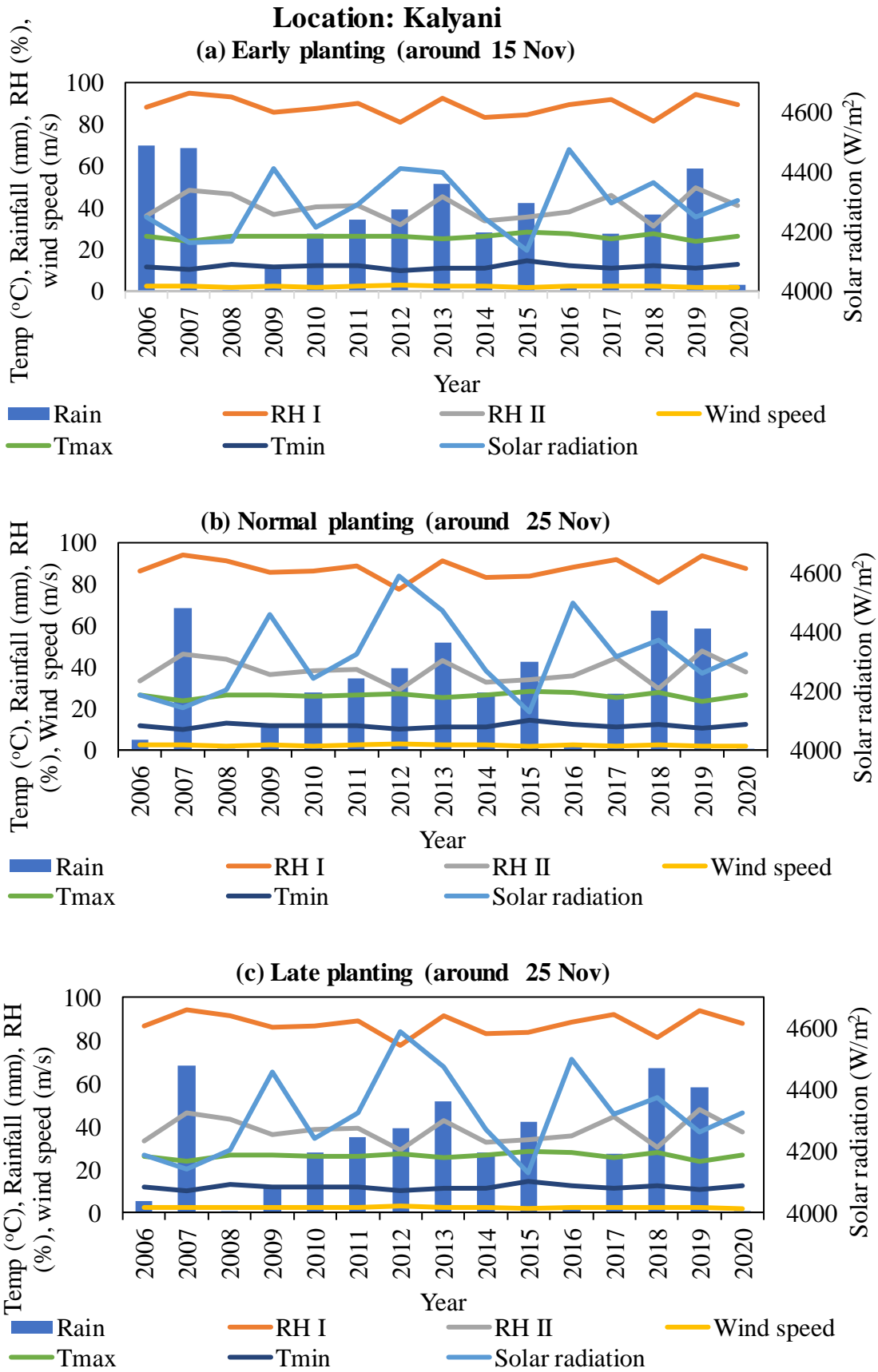


Fig 4.2 Variations in weather parameters with year for different plantings (a) Early, (b) Normal and (c) Late, in Kalyani

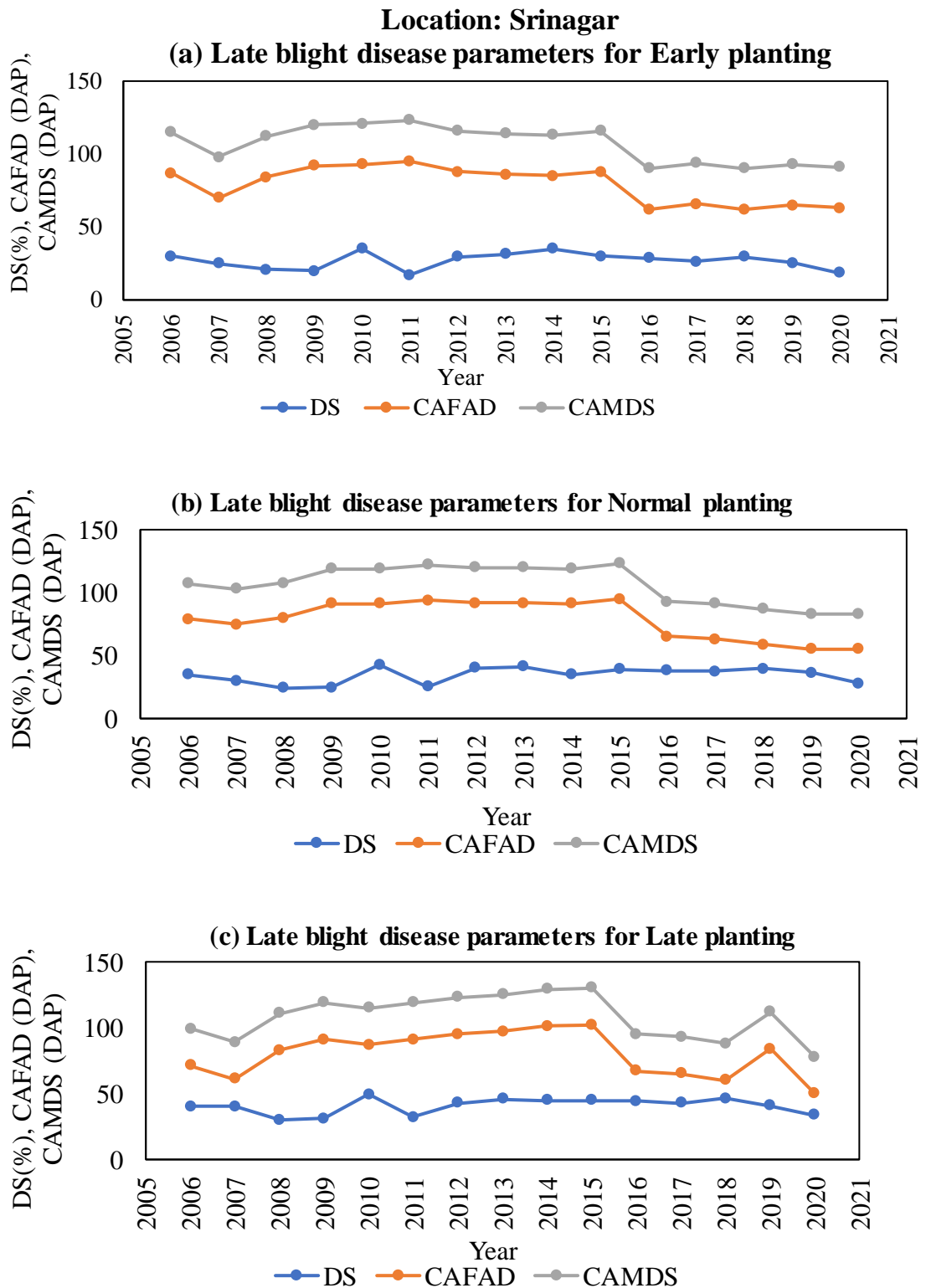


Fig 4.3 Late blight disease parameters of potato for (a) Early (b) Normal and (c) Late planting conditions in Srinagar

Location: Kalyani

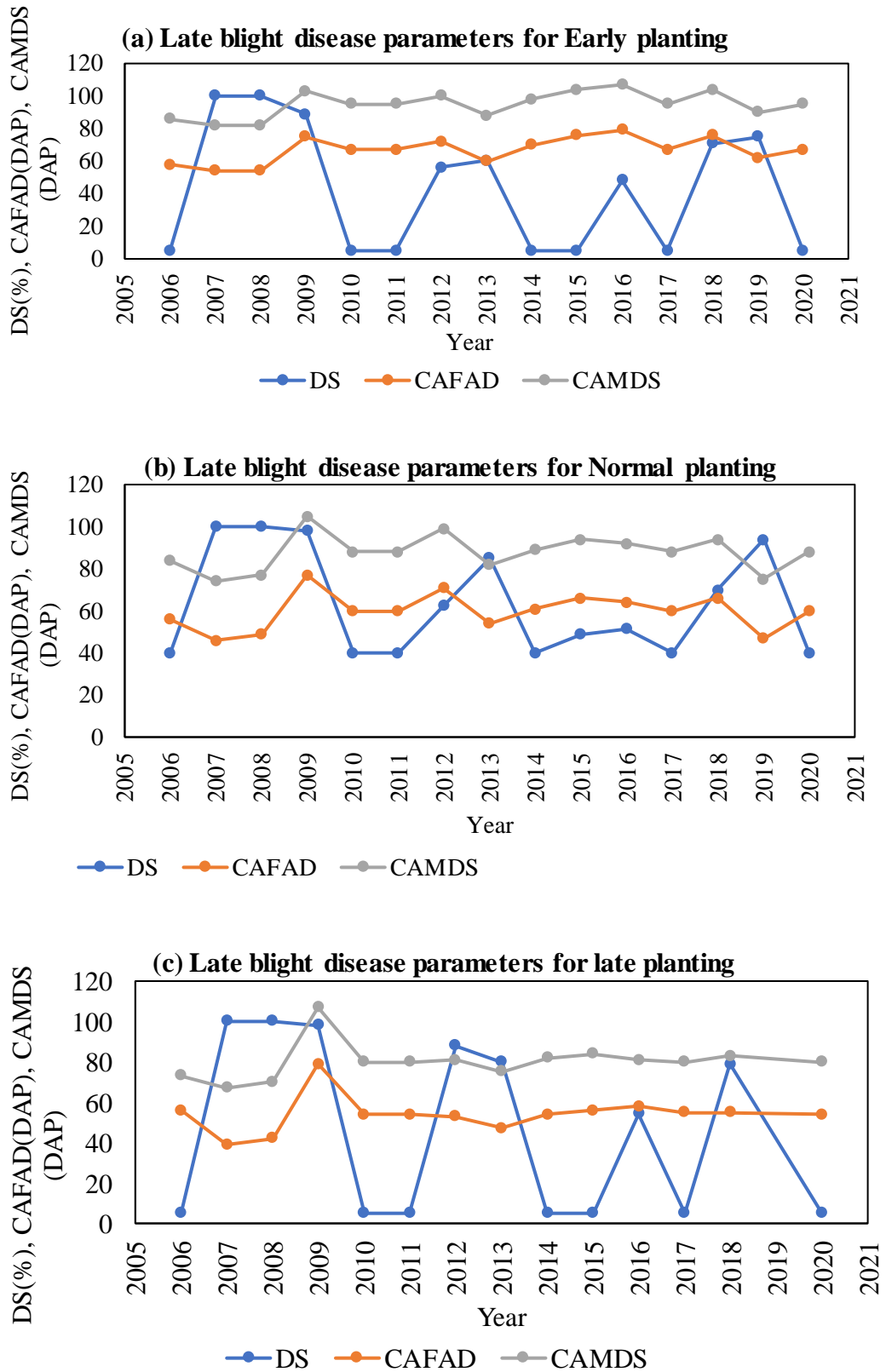


Fig 4.4 Late blight disease parameters of potato for (a) Early (b) Normal and (c) Late planting conditions in Kalyani

Disease Severity: Srinagar – Early Planting

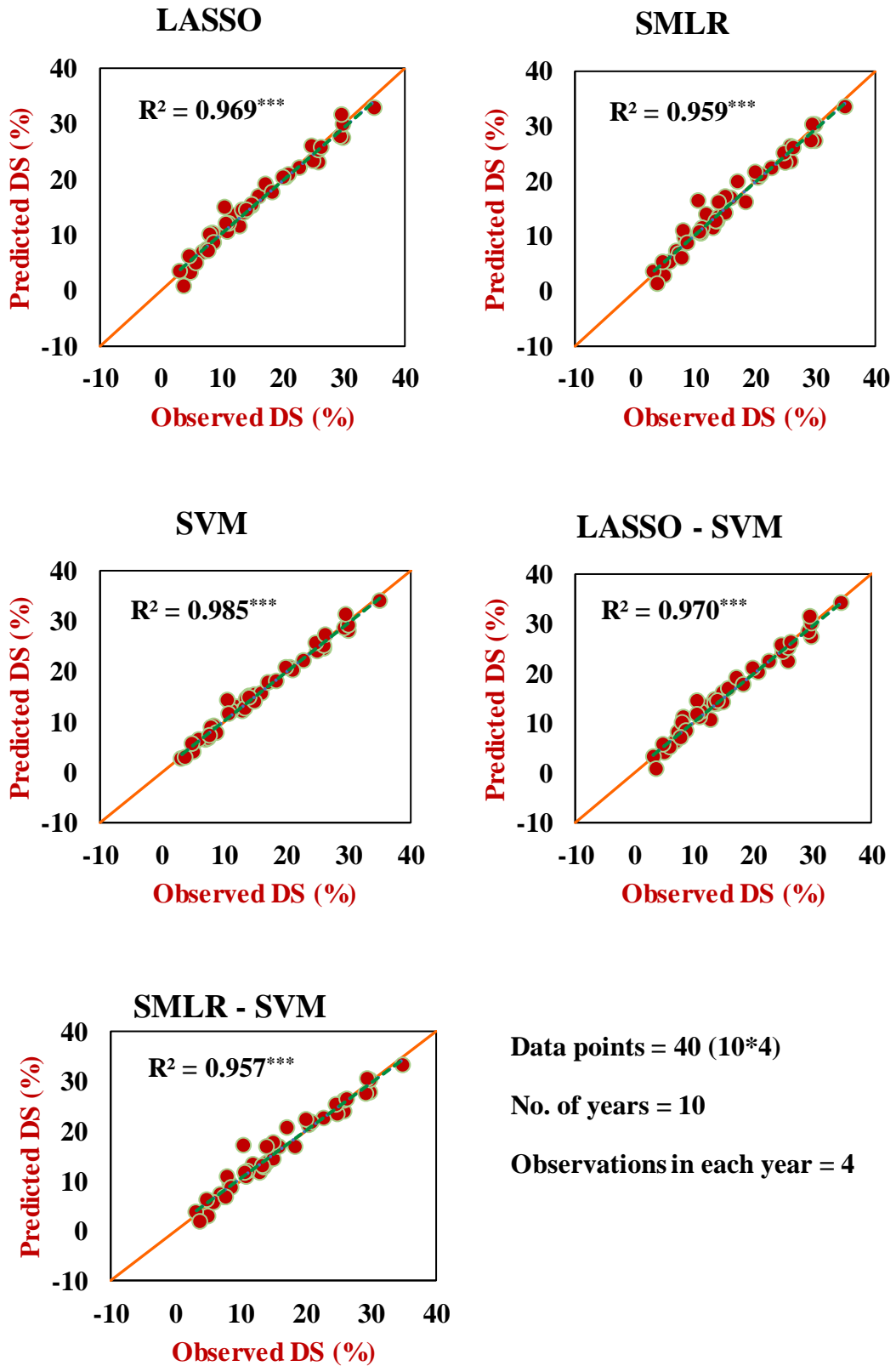


Fig 4.5 Calibration of disease severity (DS) for Early Planting for Srinagar, *** = $P < 0.001$

Disease Severity: Srinagar – Normal Planting

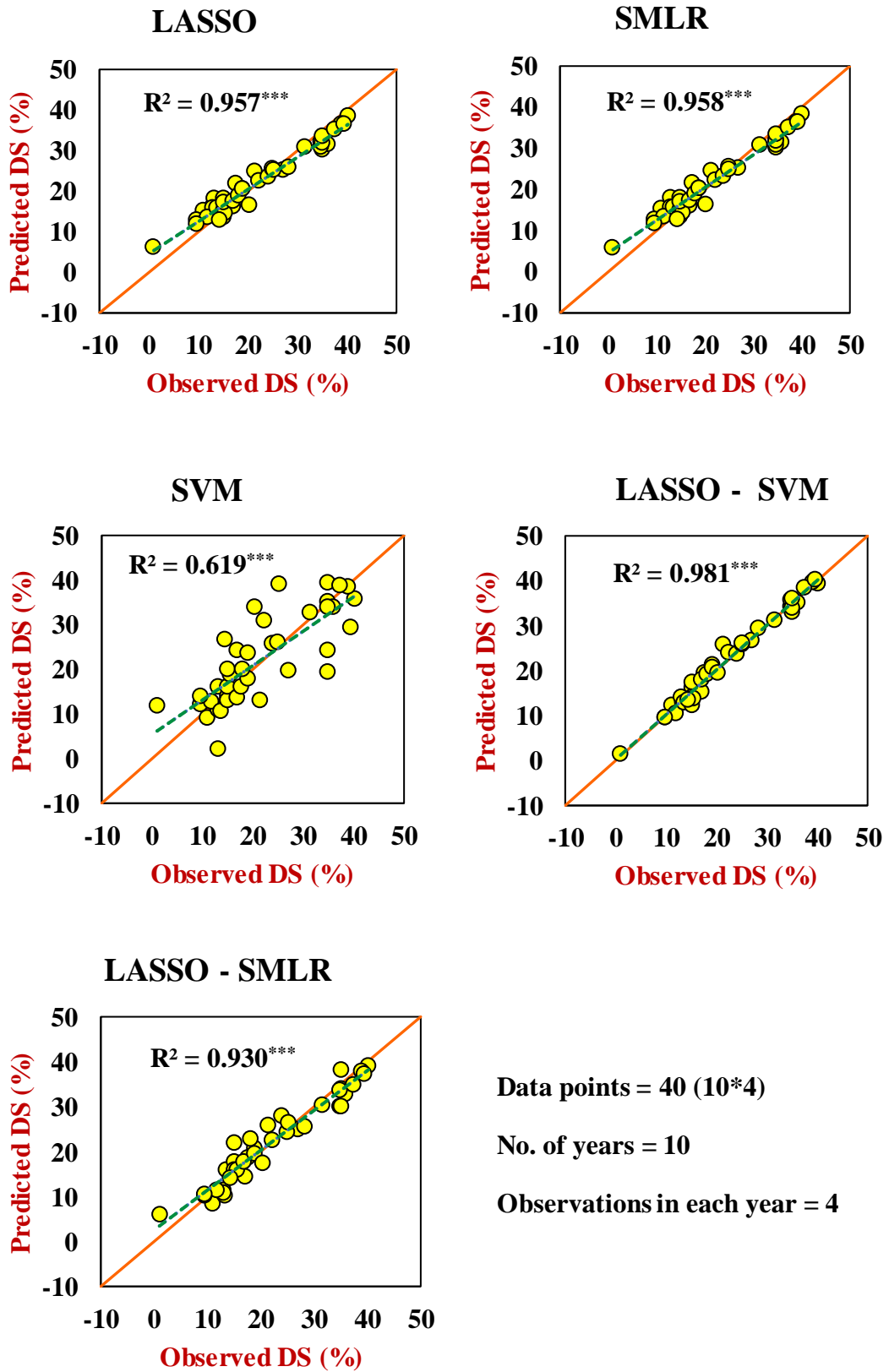


Fig 4.6 Calibration of disease severity (DS) for Normal Planting for Srinagar, *** = $P < 0.001$

Disease Severity: Srinagar – Late Planting

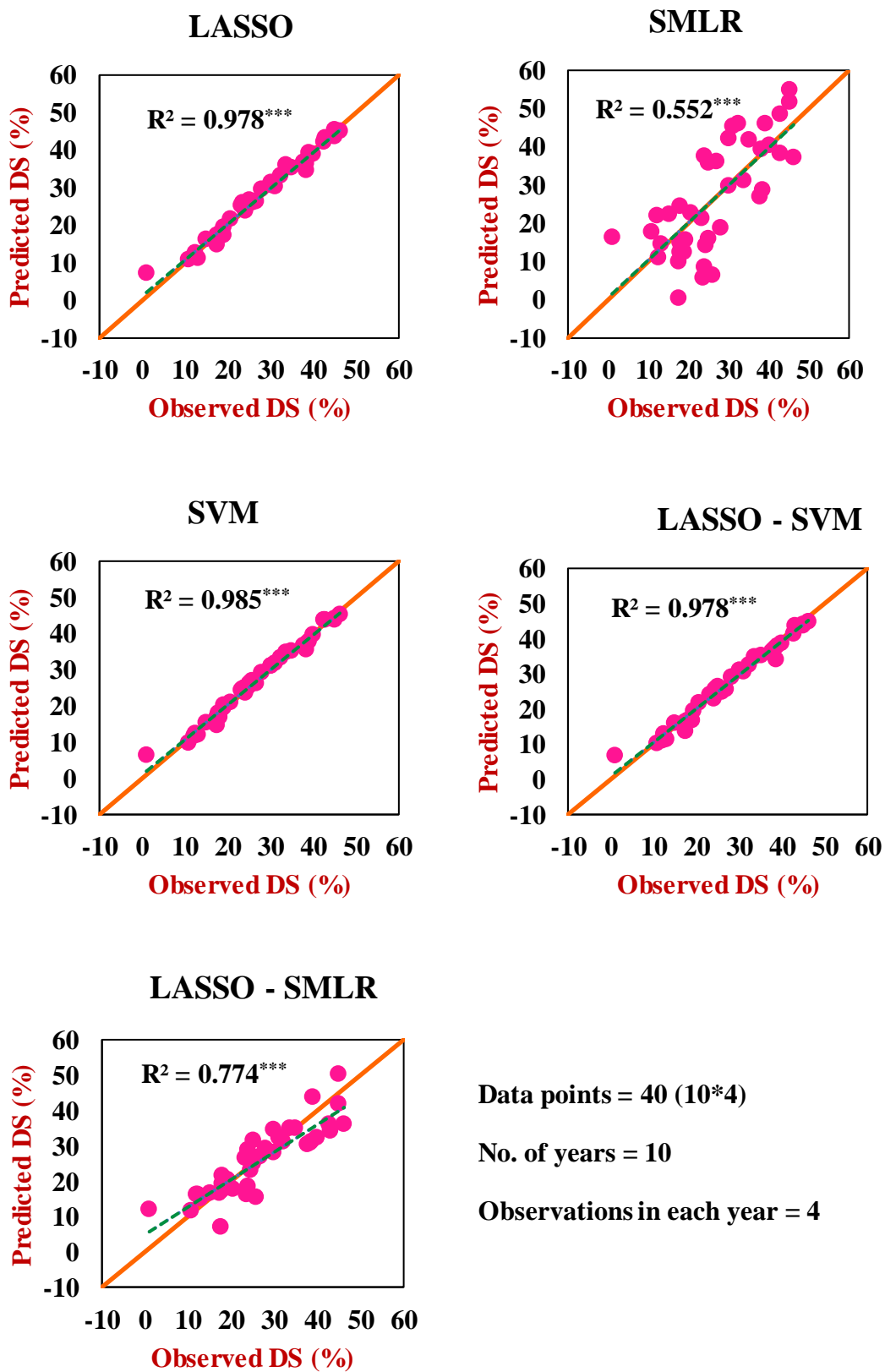


Fig 4.7 Calibration of disease severity (DS) for Late Planting for Srinagar, *** = $P < 0.001$

Disease Severity: Srinagar – All Planting (pooled data)

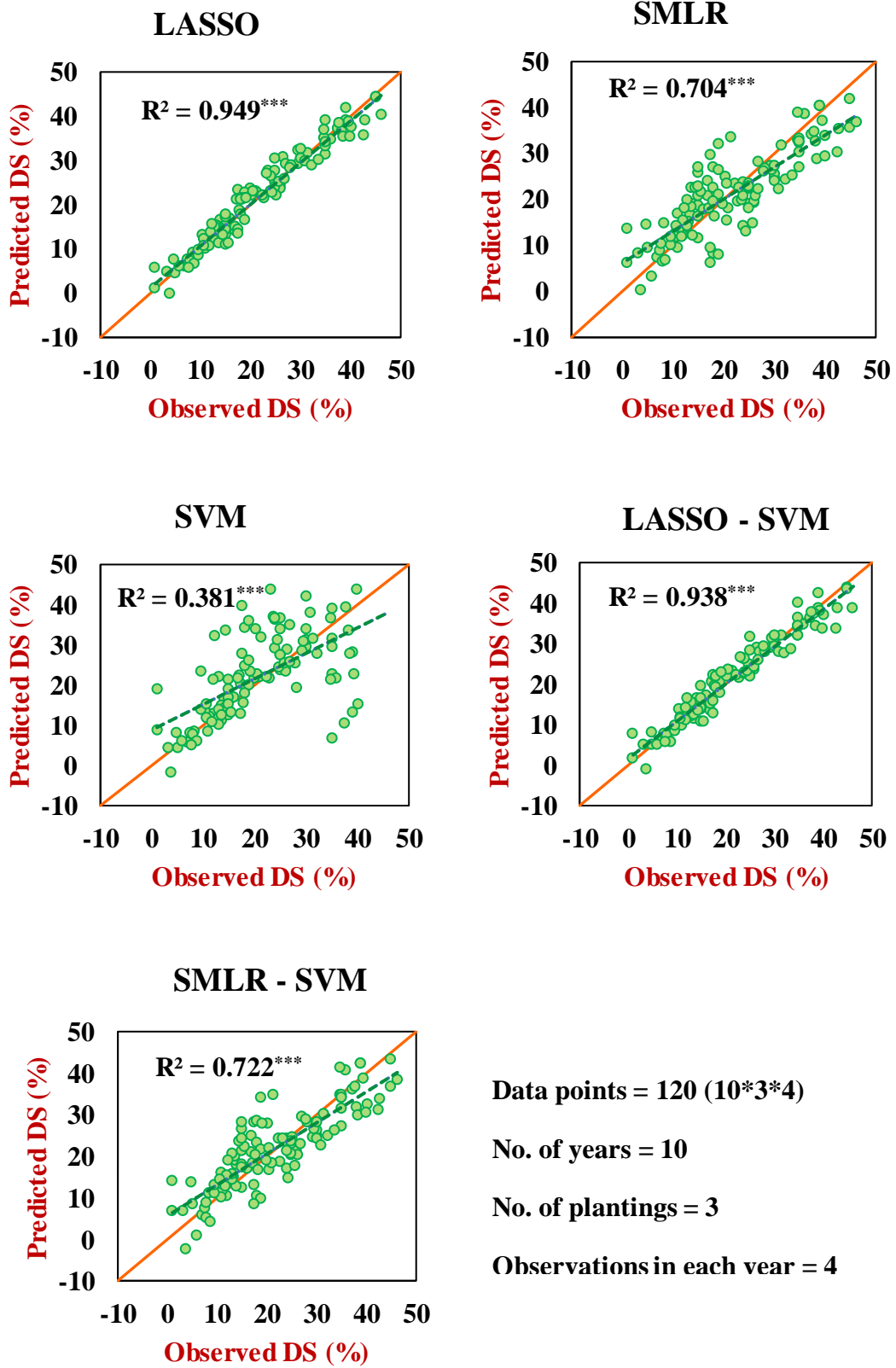


Fig 4.8 Calibration of disease severity (DS) for All Planting (pooled data) for Srinagar, = P<0.001

Disease Severity: Kalyani – Early Planting

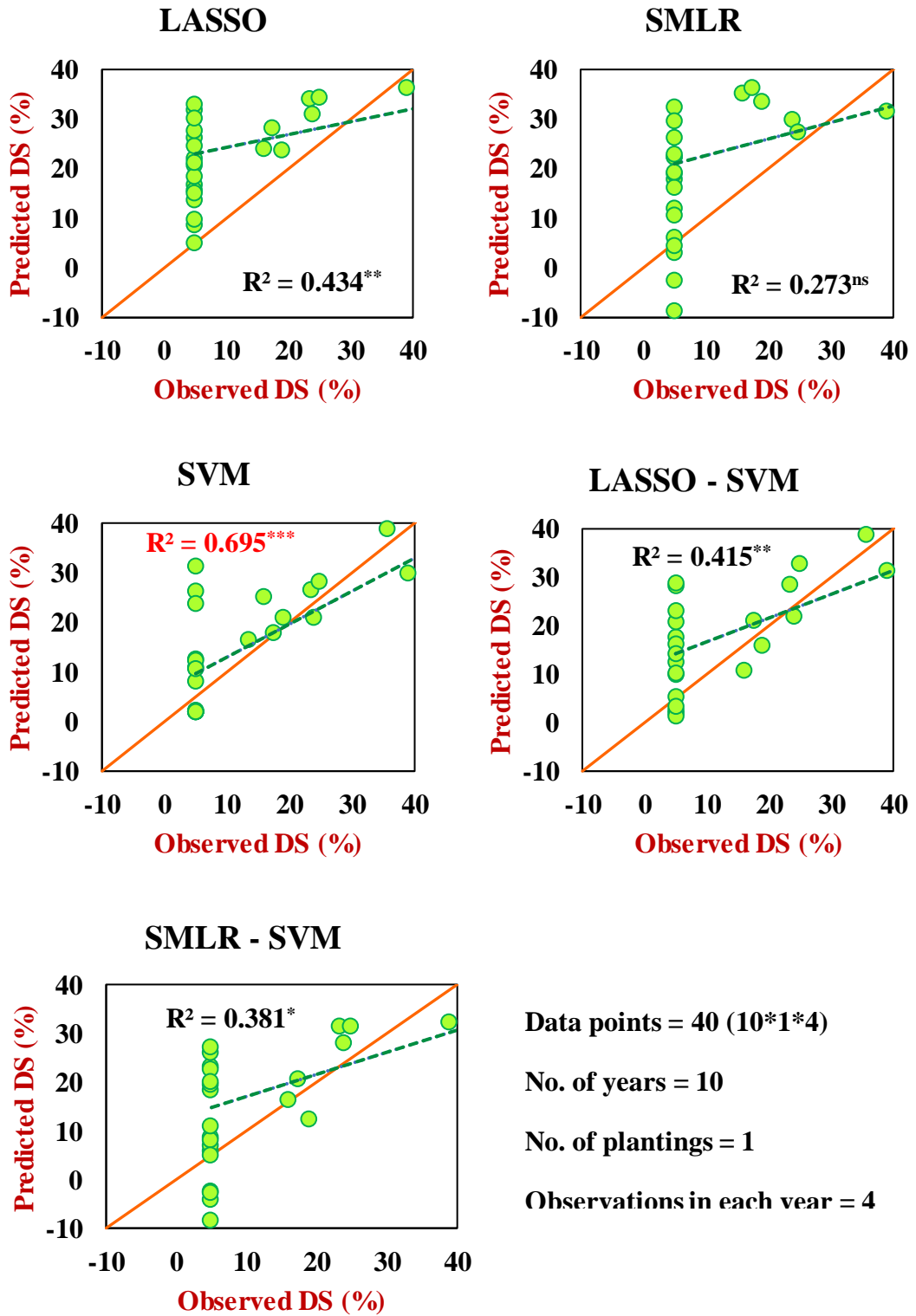


Fig 4.9 Calibration of disease severity (DS) for Early Planting for Kalyani, *** = $P < 0.001$, ** = $P < 0.01$, * = $P < 0.05$ and ns = non-significant

Disease Severity: Kalyani – Normal Planting

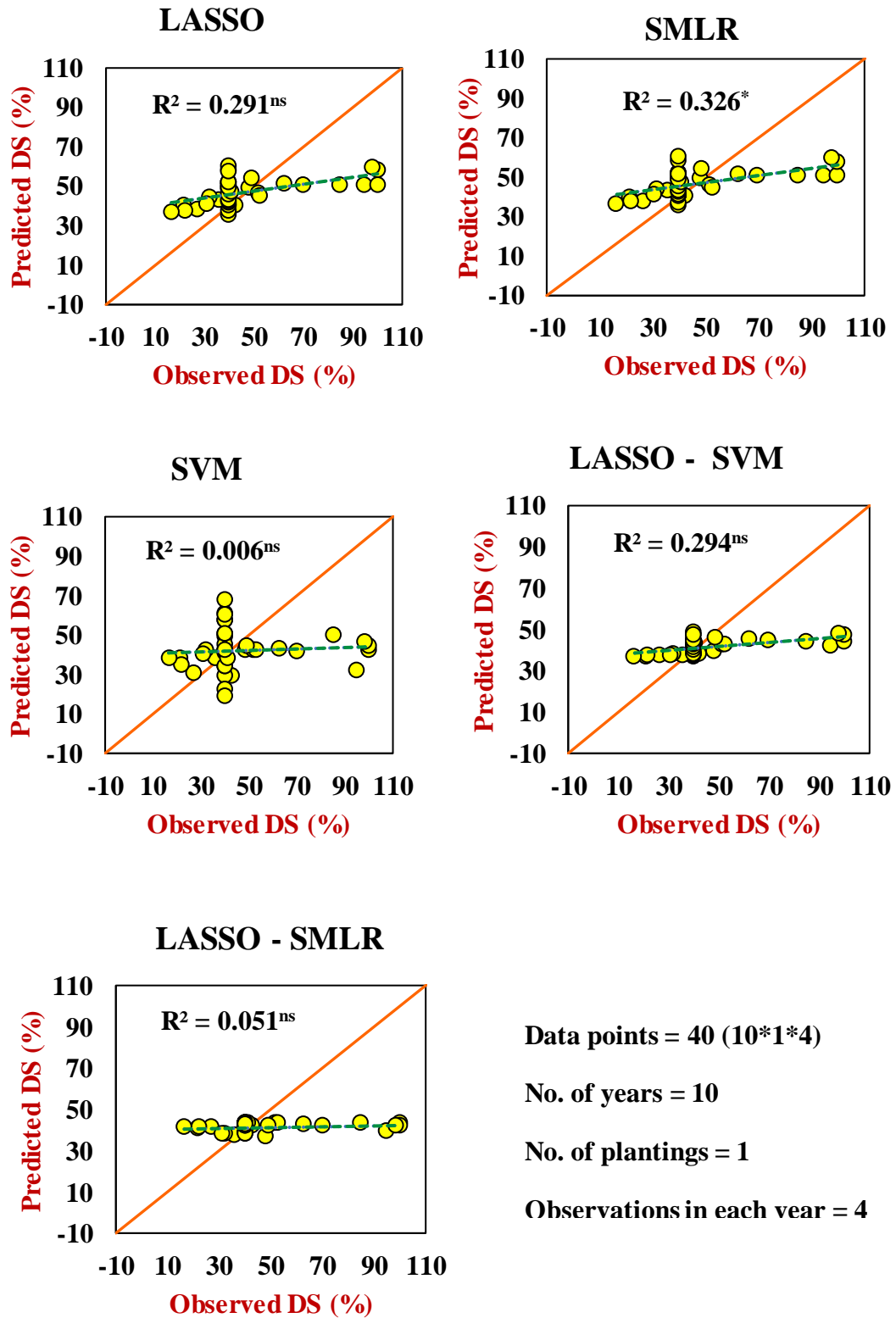


Fig 4.10 Calibration of disease severity (DS) for Normal Planting for Kalyani, ** = $P < 0.01$, and ns = non-significant

Disease Severity: Kalyani – Late Planting

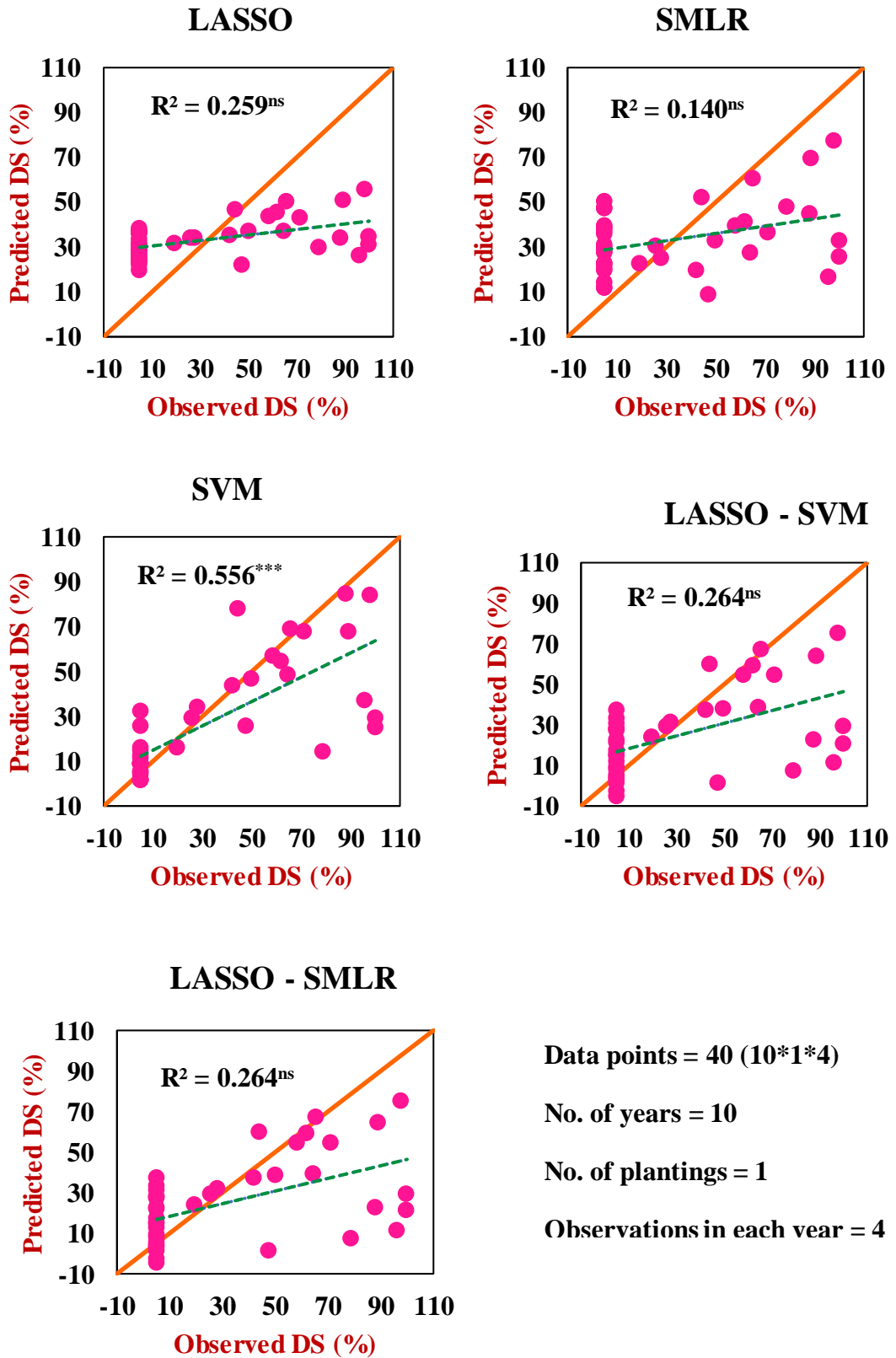


Fig 4.11 Calibration of disease severity (DS) for Late Planting for Kalyani, *** = $P < 0.001$, and ns = non-significant

Disease Severity: Kalyani – All Planting (pooled data)

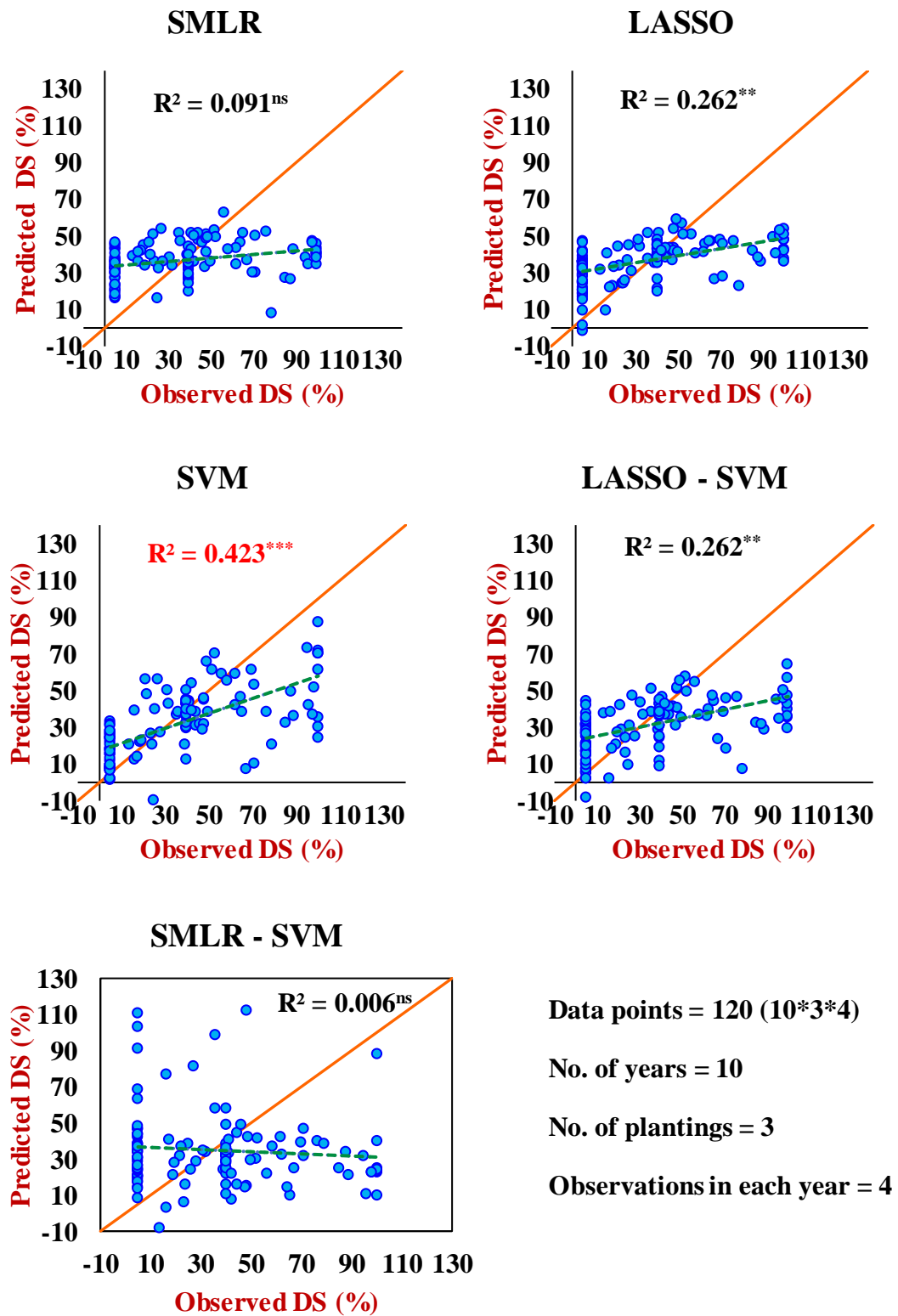


Fig 4.12 Calibration of disease severity (DS) for All Planting for Kalyani, *** = $P < 0.001$, ** = $P < 0.01$ and ns = non-significant

**Crop Age at First Appearance of Disease (CAFAD):
Srinagar – Early Planting**

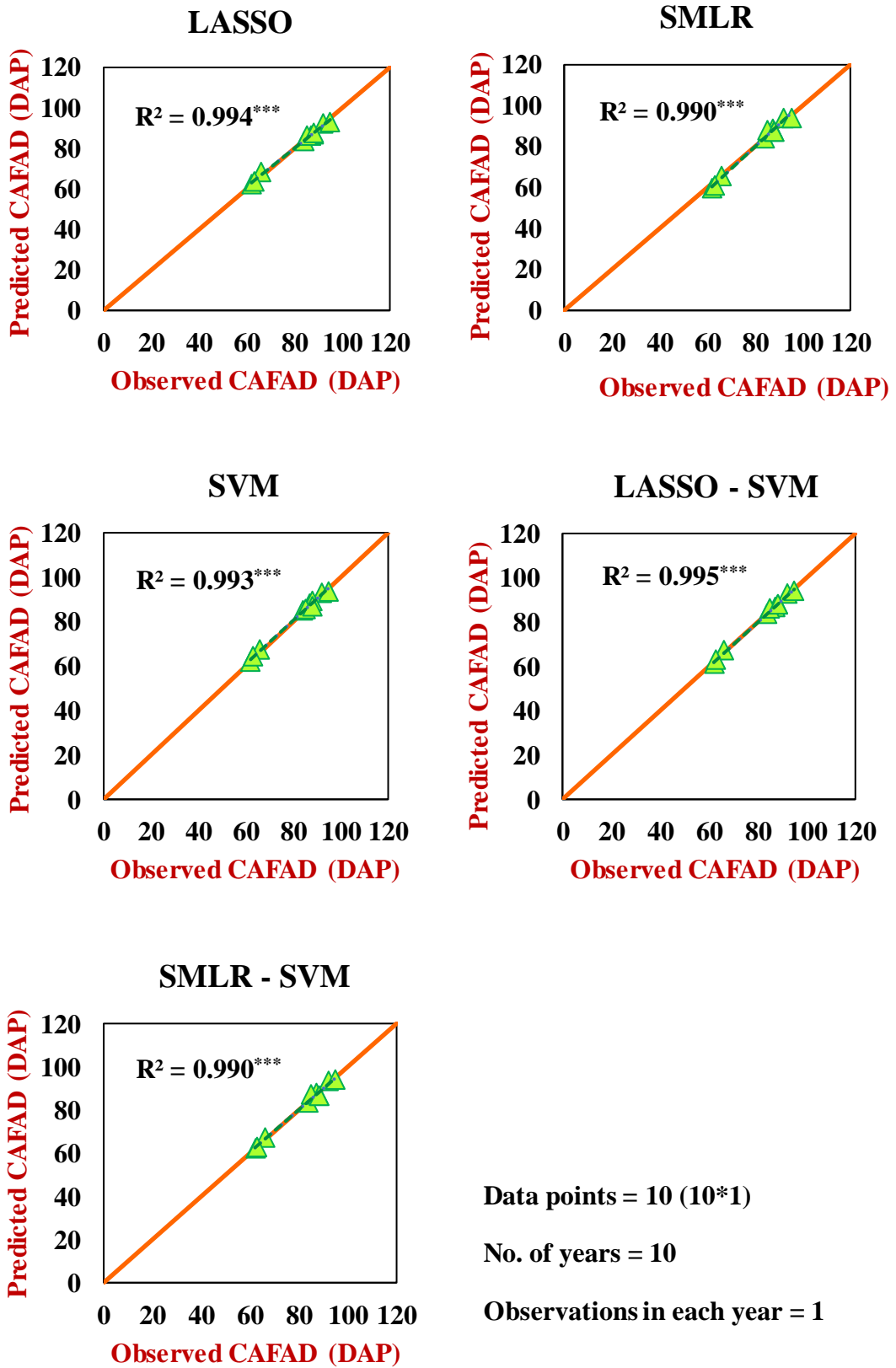


Fig 4.13 Calibration of Crop Age at First Appearance of Disease (CAFAD) for Early Planting for Srinagar, DAP-Days After Planting, *** = P<0.001

**Crop Age at First Appearance of Disease (CAFAD):
Srinagar – Normal Planting**

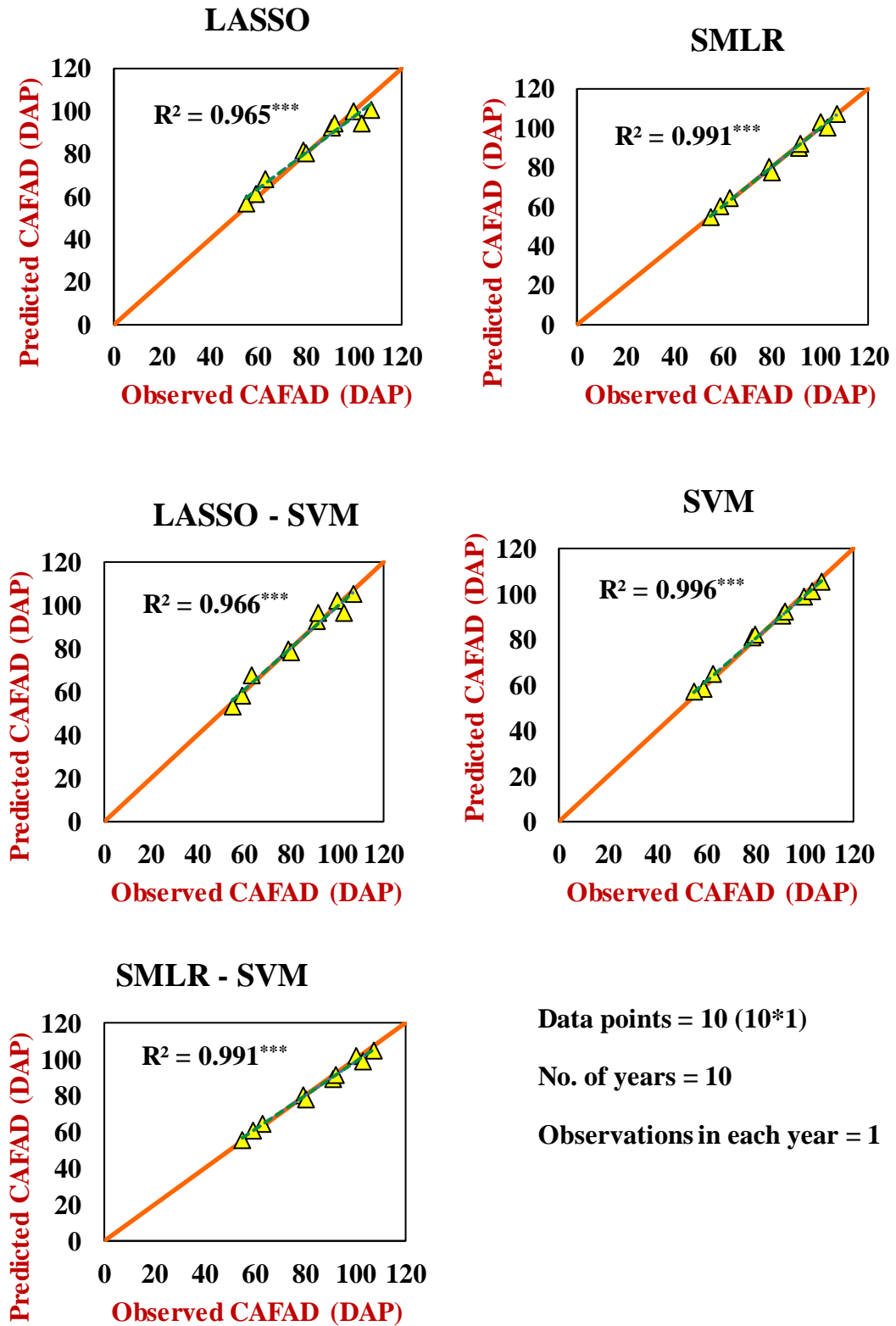


Fig 4.14 Calibration of Crop Age at First Appearance of Disease (CAFAD) for Normal Planting for Srinagar, DAP-Days After Planting, *** = P<0.001

**Crop Age at First Appearance of Disease (CAFAD):
Srinagar – Late Planting**

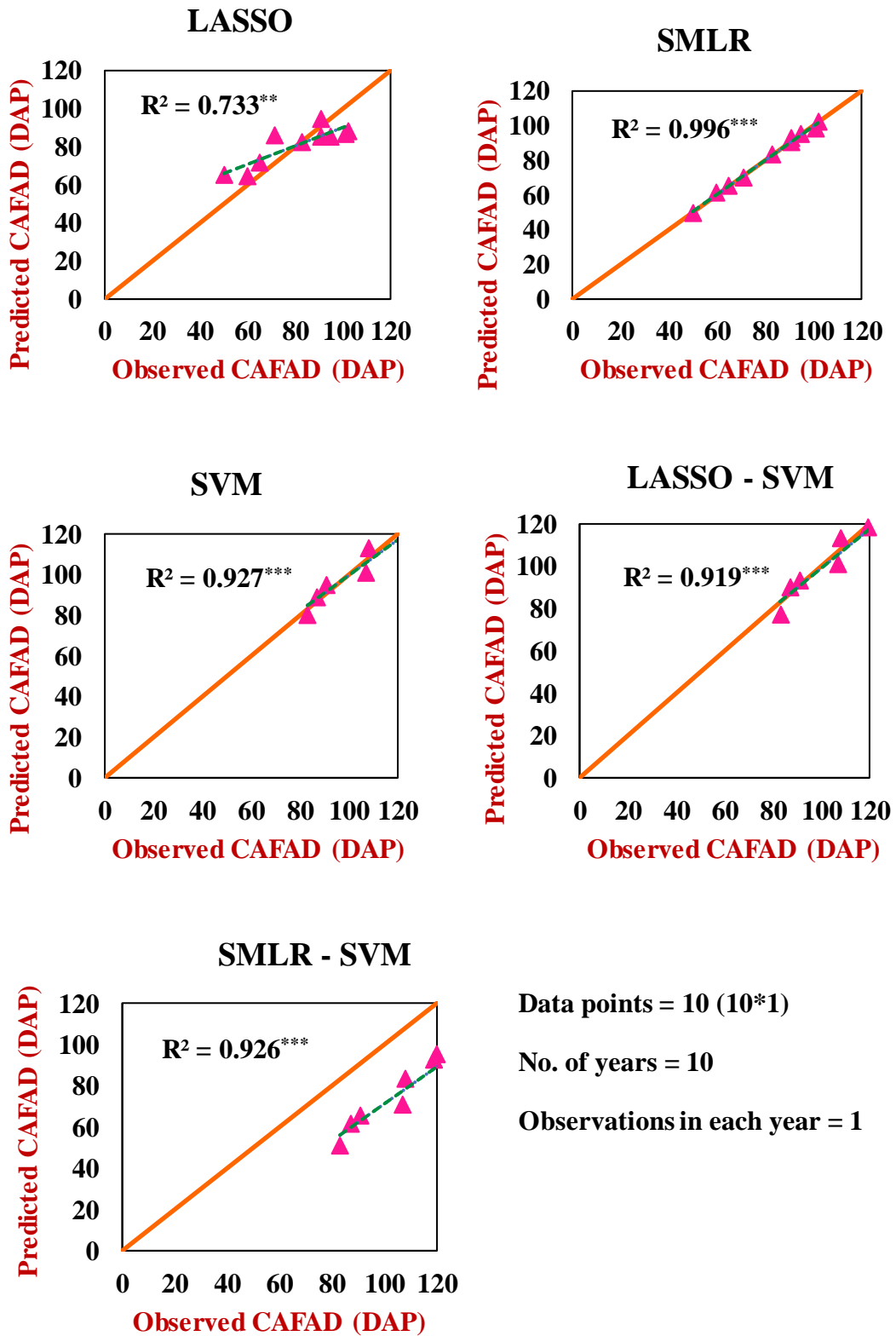


Fig 4.15 Calibration of Crop Age at First Appearance of Disease (CAFAD) for Late Planting for Srinagar, DAP-Days After Planting, *** = $P < 0.001$

**Crop Age at First Appearance of Disease (CAFAD):
Srinagar – All Planting**

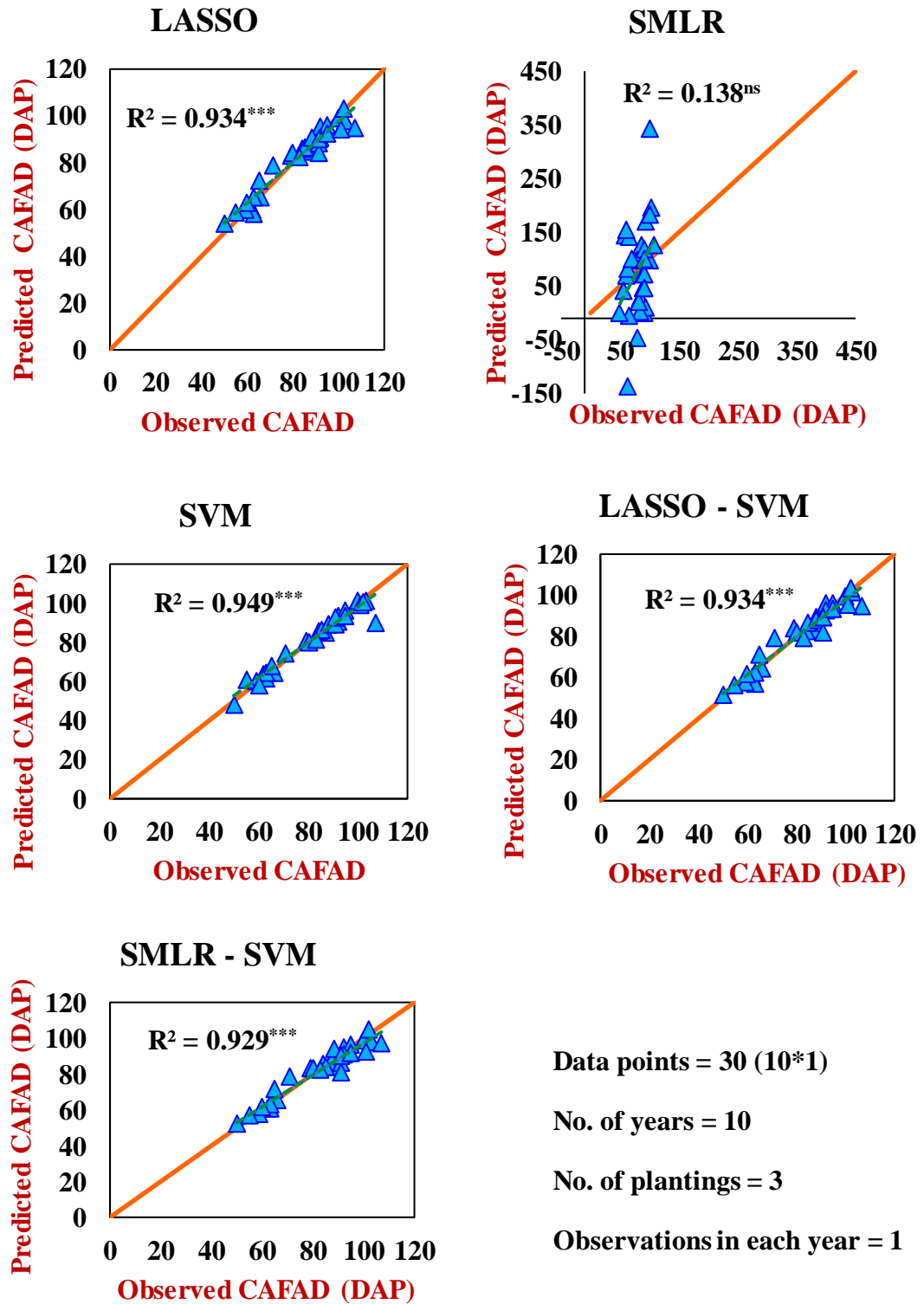


Fig. 4.16 Calibration of Crop Age at First Appearance of Disease (CAFAD) for All Planting (pooled data) for Srinagar, DAP-Days After Planting, *** = $P < 0.001$ and ns = non-significant

Crop Age at First Appearance of Disease (CAFAD): Kalyani – Early Planting

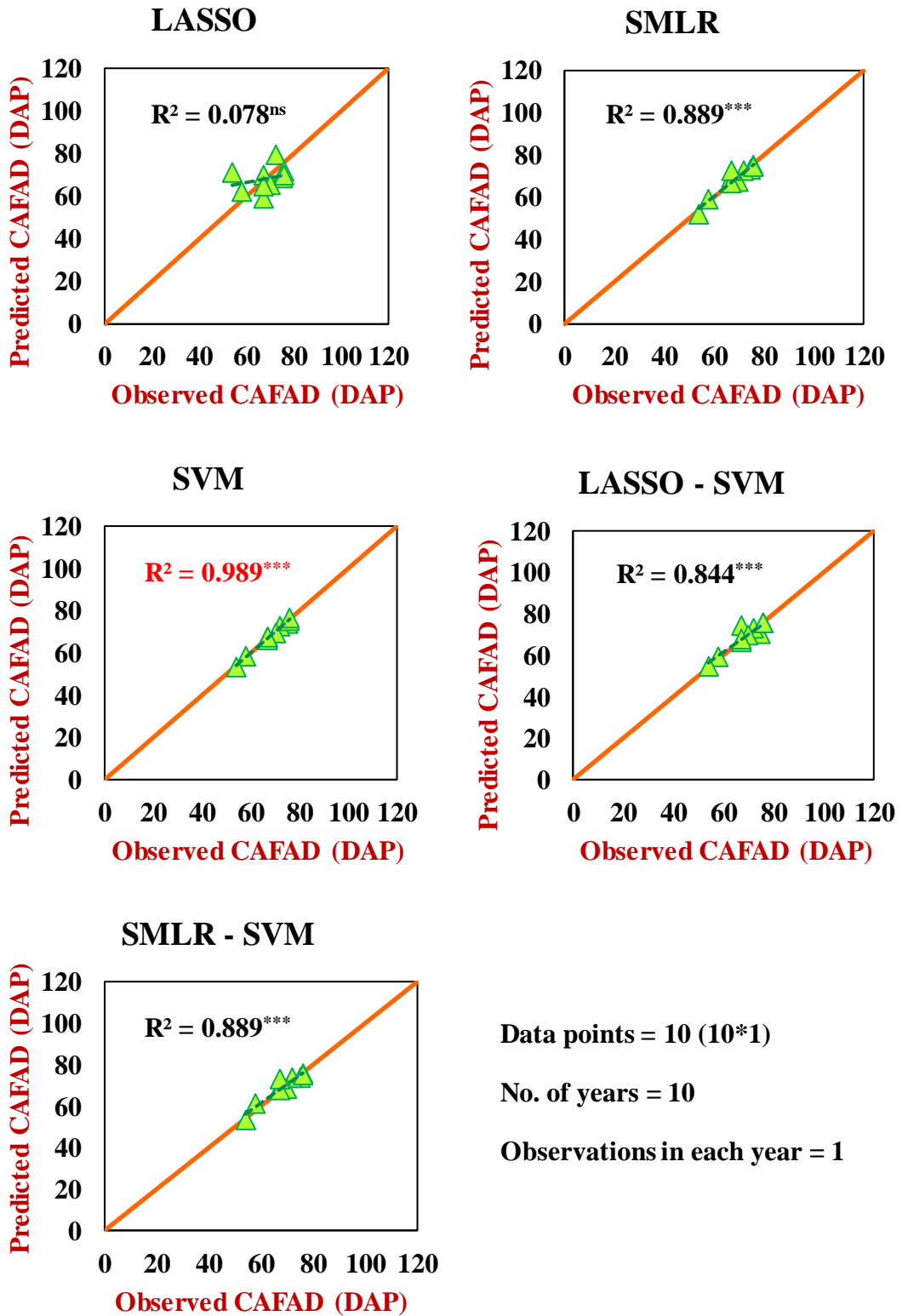


Fig. 4.17 Calibration of Crop Age at First Appearance of Disease (CAFAD) for early planting at Kalyani, DAP-Days After Planting, *** = $P < 0.001$, and ns = non-significant

Crop Age at First Appearance of Disease (CAFAD): Kalyani – Normal Planting

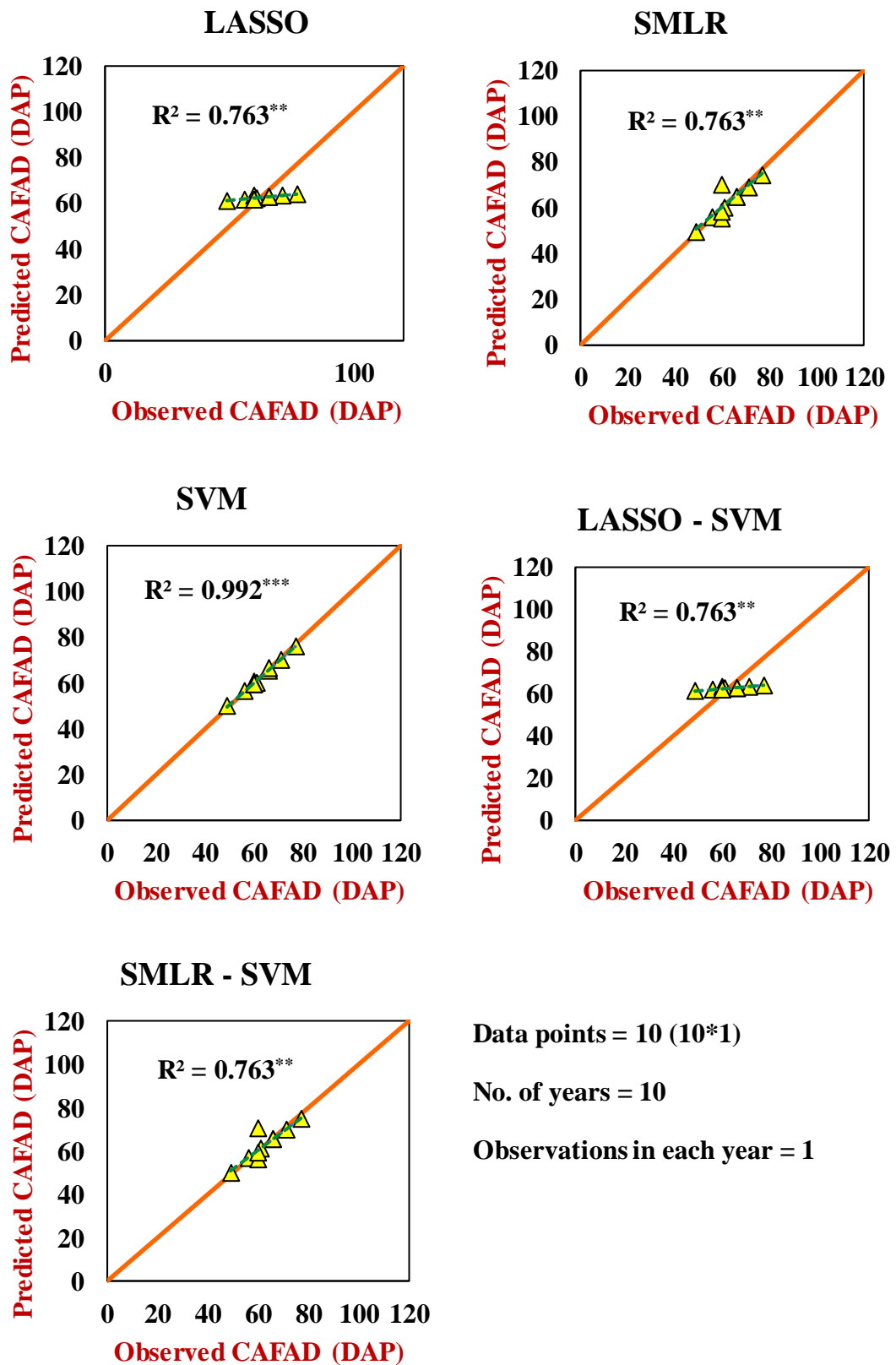


Fig. 4.18 Calibration of Crop Age at First Appearance of Disease (CAFAD) for Normal planting at Kalyani, DAP-Days After Planting, *** = $P < 0.001$, ** = $P < 0.01$

Crop Age at First Appearance of Disease (CAFAD): Kalyani – Late Planting

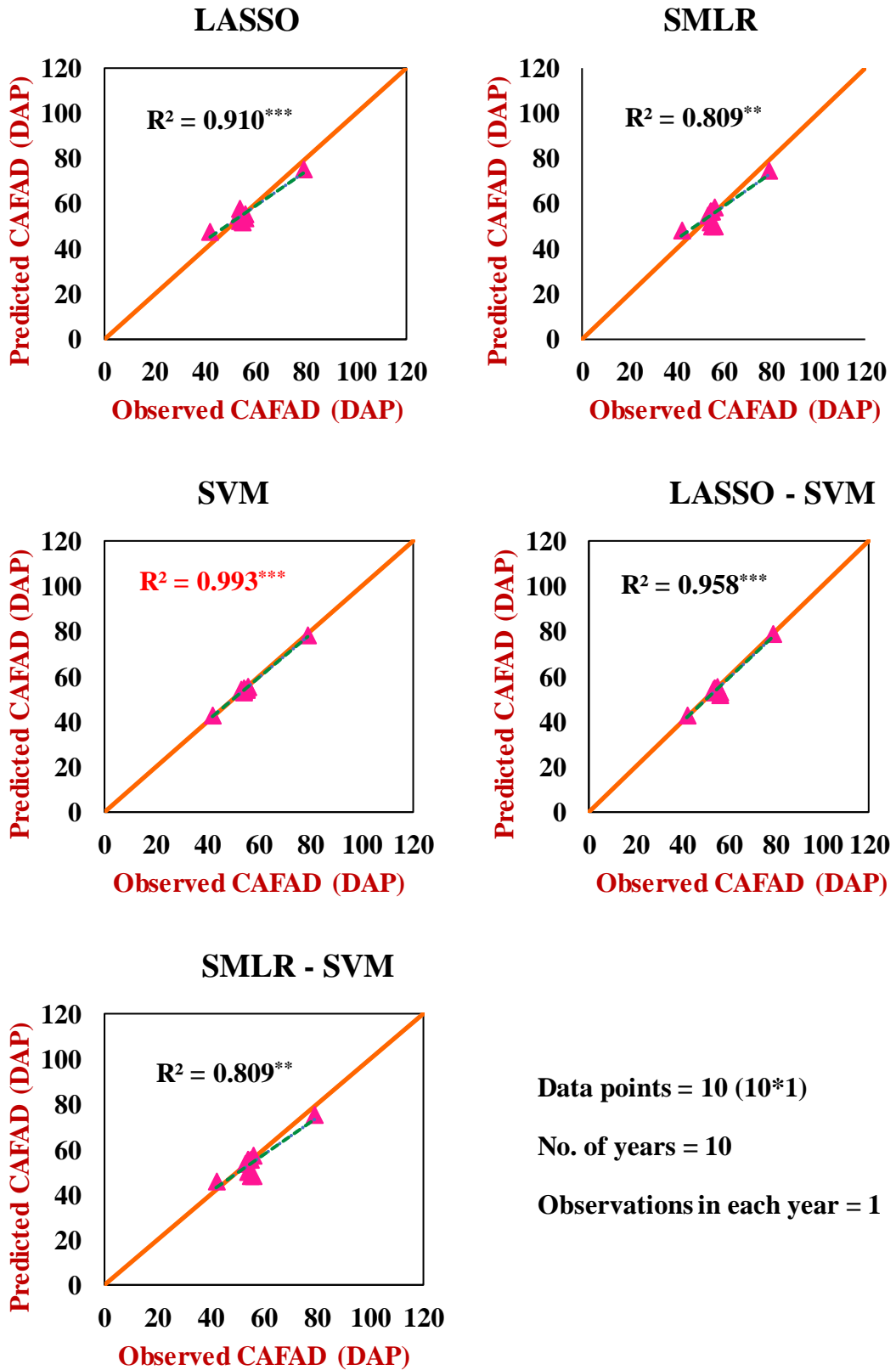


Fig. 4.19 Calibration of Crop Age at First Appearance of Disease (CAFAD) for Late planting at Kalyani, DAP-Days After Planting, *** = P<0.001, ** = P<0.01

Crop Age at First Appearance of Disease (CAFAD): Kalyani – All Planting

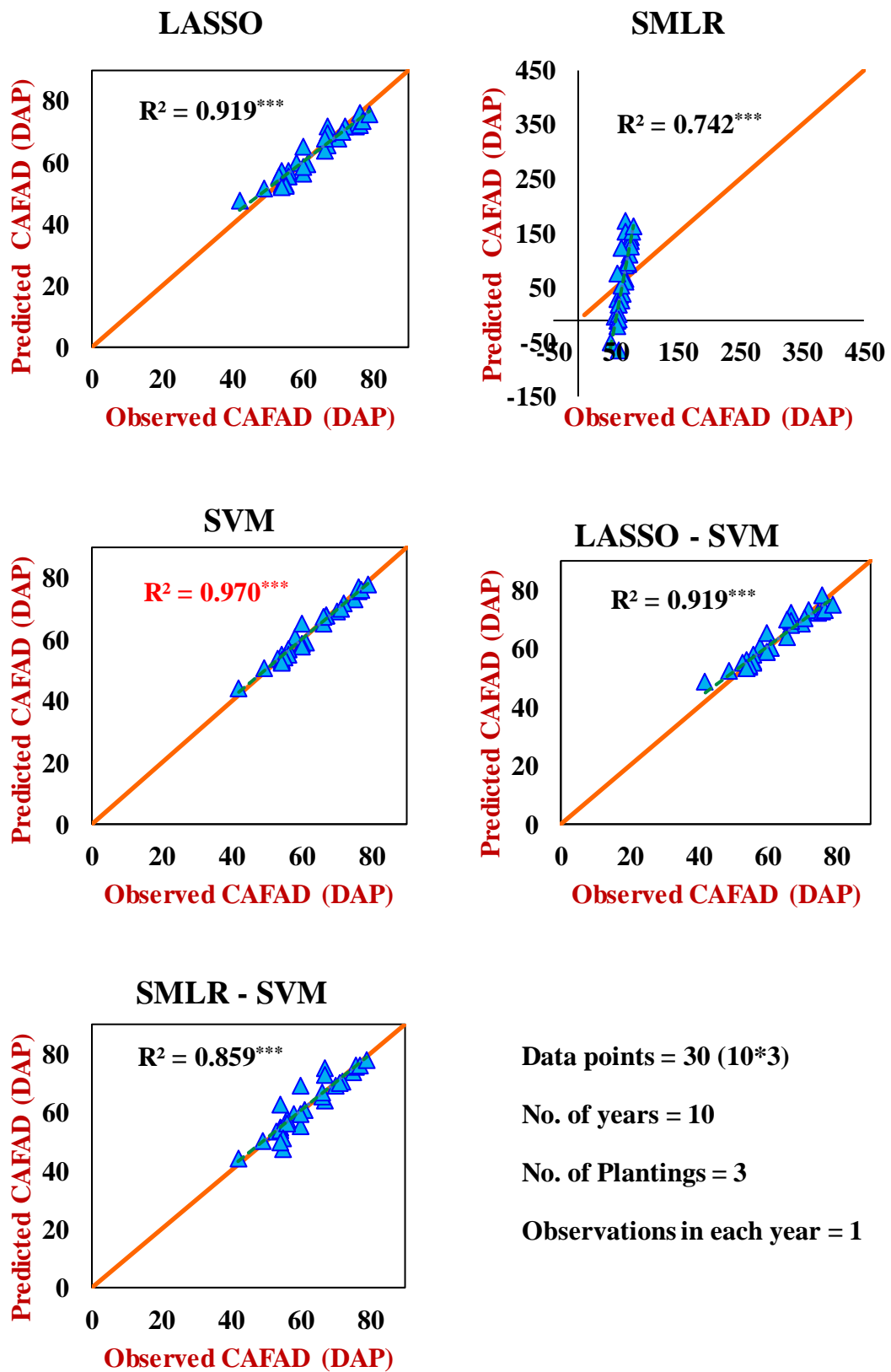


Fig. 4.20 Calibration of Crop Age at First Appearance of Disease (CAFAD) for All planting at Kalyani, DAP-Days After Planting, *** = $P < 0.001$

Crop Age at Maximum Disease Severity (CAMDS): Srinagar – Early Planting

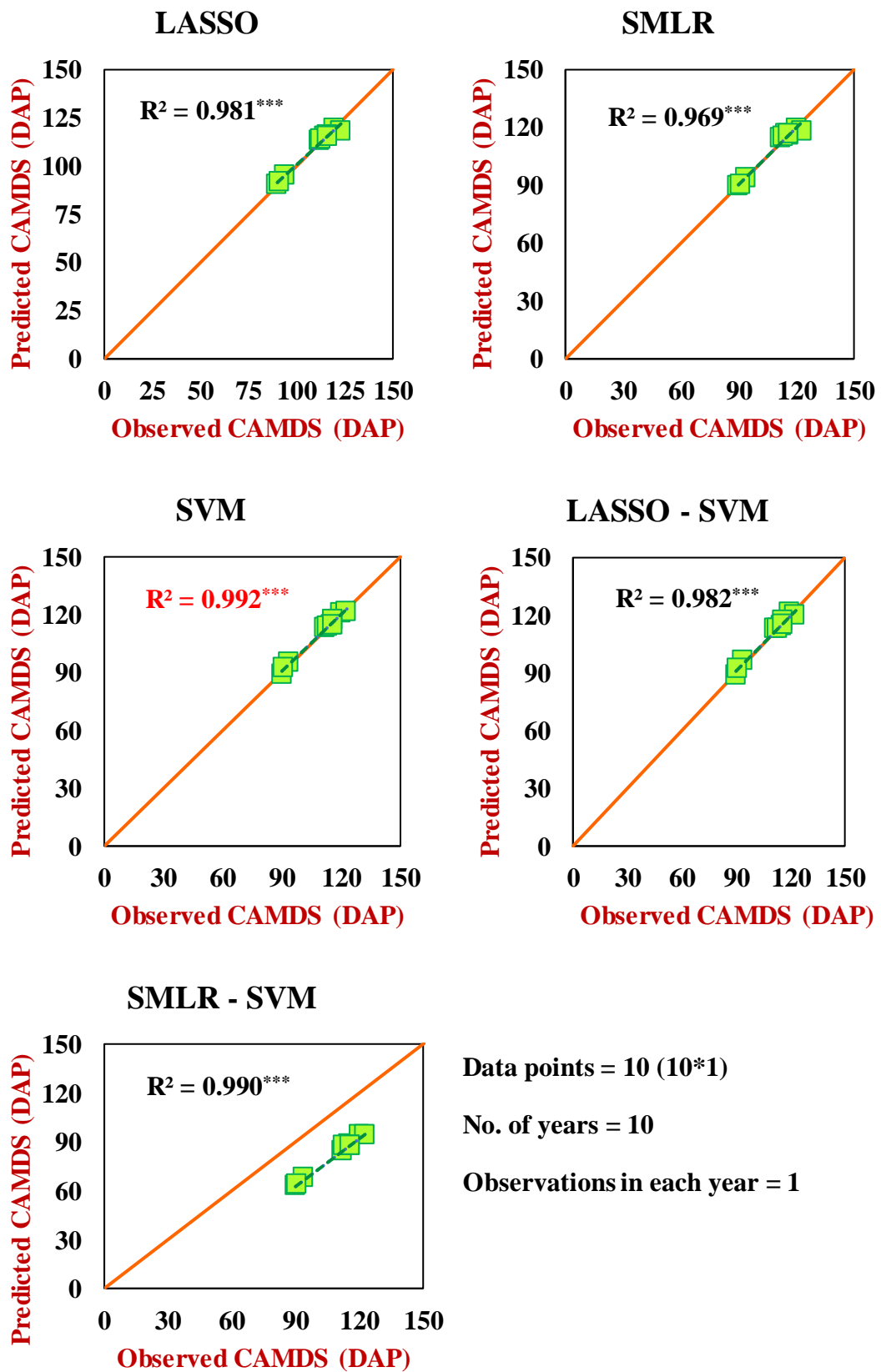


Fig. 4.21 Calibration of Crop Age at Maximum Disease Severity (CAMDS) for Early planting at Srinagar, DAP-Days After Planting, *** = $P < 0.001$

Crop Age at Maximum Disease Severity (CAMDS): Srinagar – Normal Planting

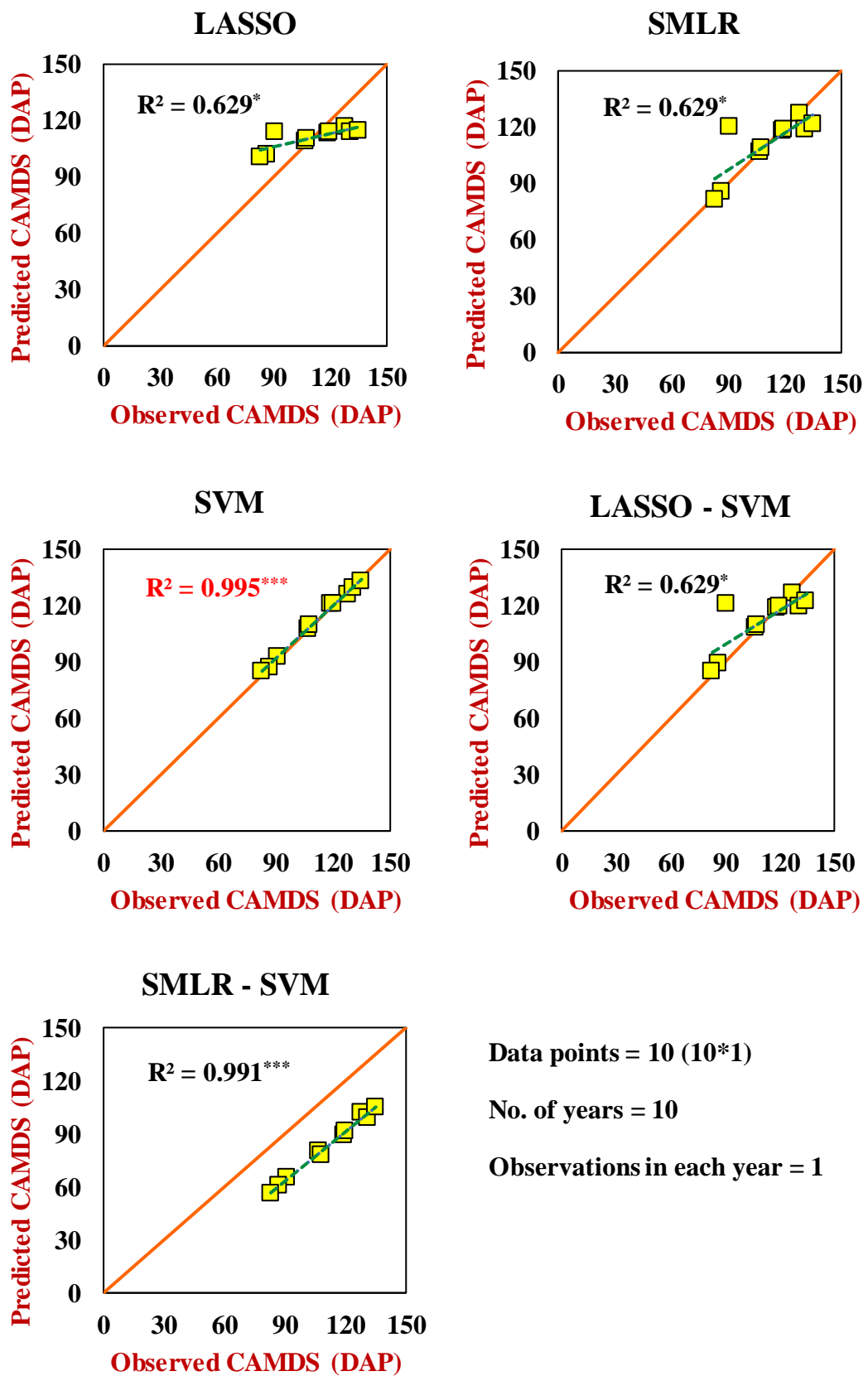


Fig. 4.22 Calibration of Crop Age at Maximum Disease Severity (CAMDS) for Normal planting at Srinagar, DAP-Days After Planting, *** = $P < 0.001$, * = $P < 0.05$

Crop Age at Maximum Disease Severity (CAMDS): Srinagar – Late Planting

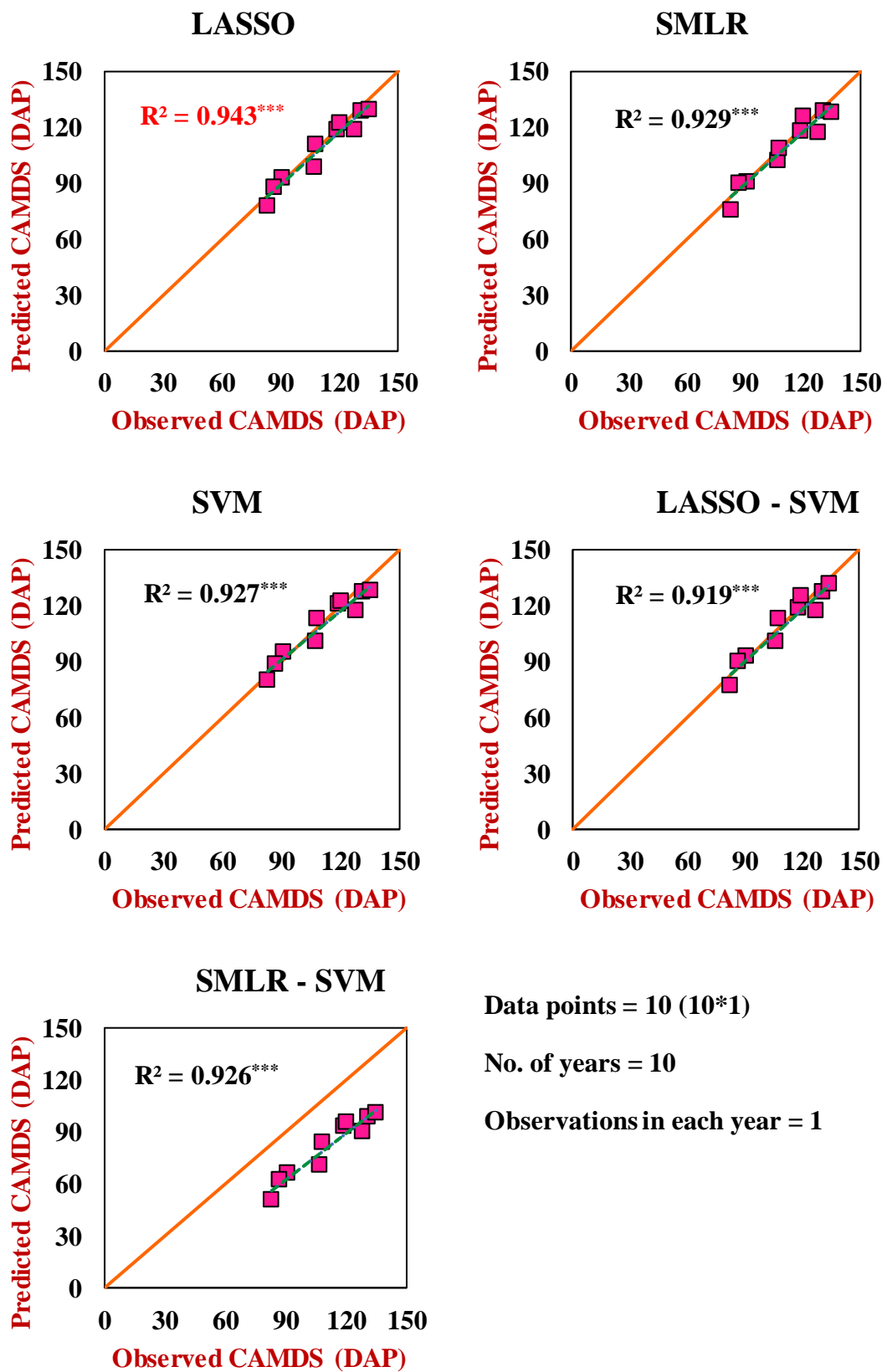


Fig. 4.23 Calibration of Crop Age at Maximum Disease Severity (CAMDS) for late planting at Srinagar, DAP-Days After Planting, *** = $P < 0.001$

Crop Age at Maximum Disease Severity (CAMDS): Srinagar – All Planting

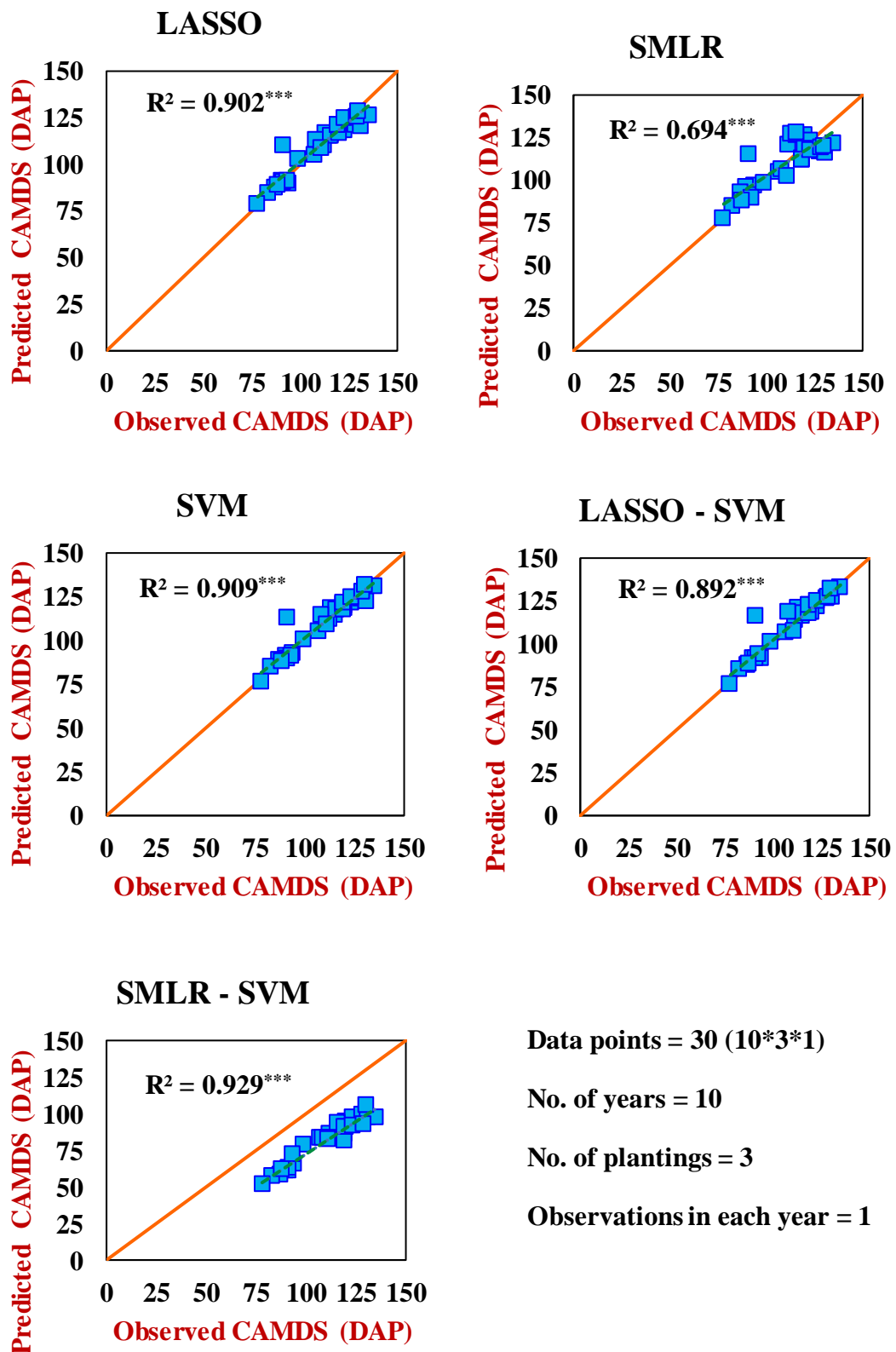


Fig. 4.24 Calibration of Crop Age at Maximum Disease Severity (CAMDS) for All planting (pooled data) at Srinagar, DAP-Days After Planting, *** = $P < 0.001$, * = $P < 0.05$

Crop Age at Maximum Disease Severity (CAMDS): Kalyani – Early Planting

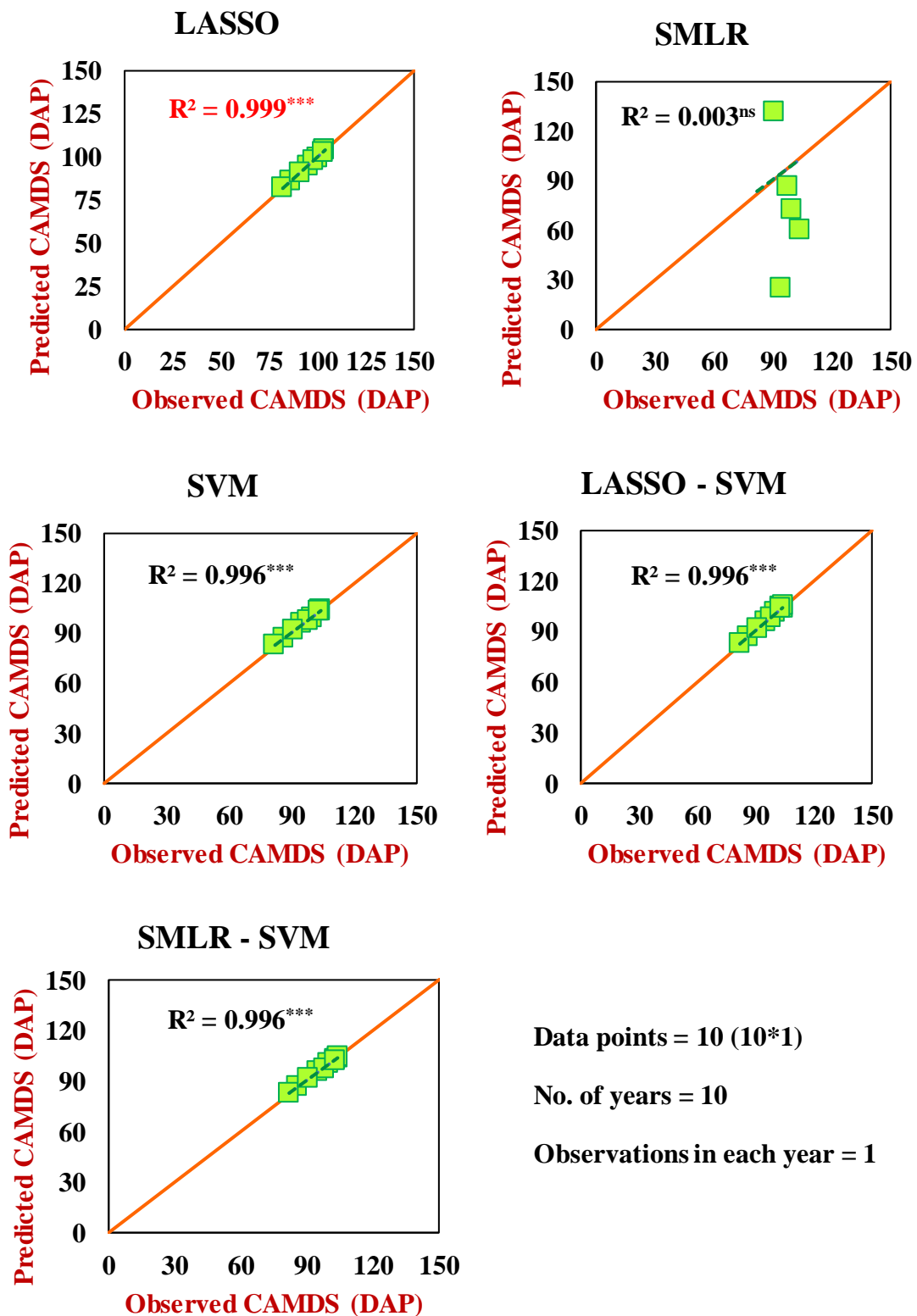


Fig. 4.25 Calibration of Crop Age at Maximum Disease Appearance (CAMDS) for early planting at Kalyani, DAP-Days After Planting, *** = $P < 0.001$, ns = non-significant

Crop Age at Maximum Disease Severity (CAMDS): Kalyani – Normal Planting

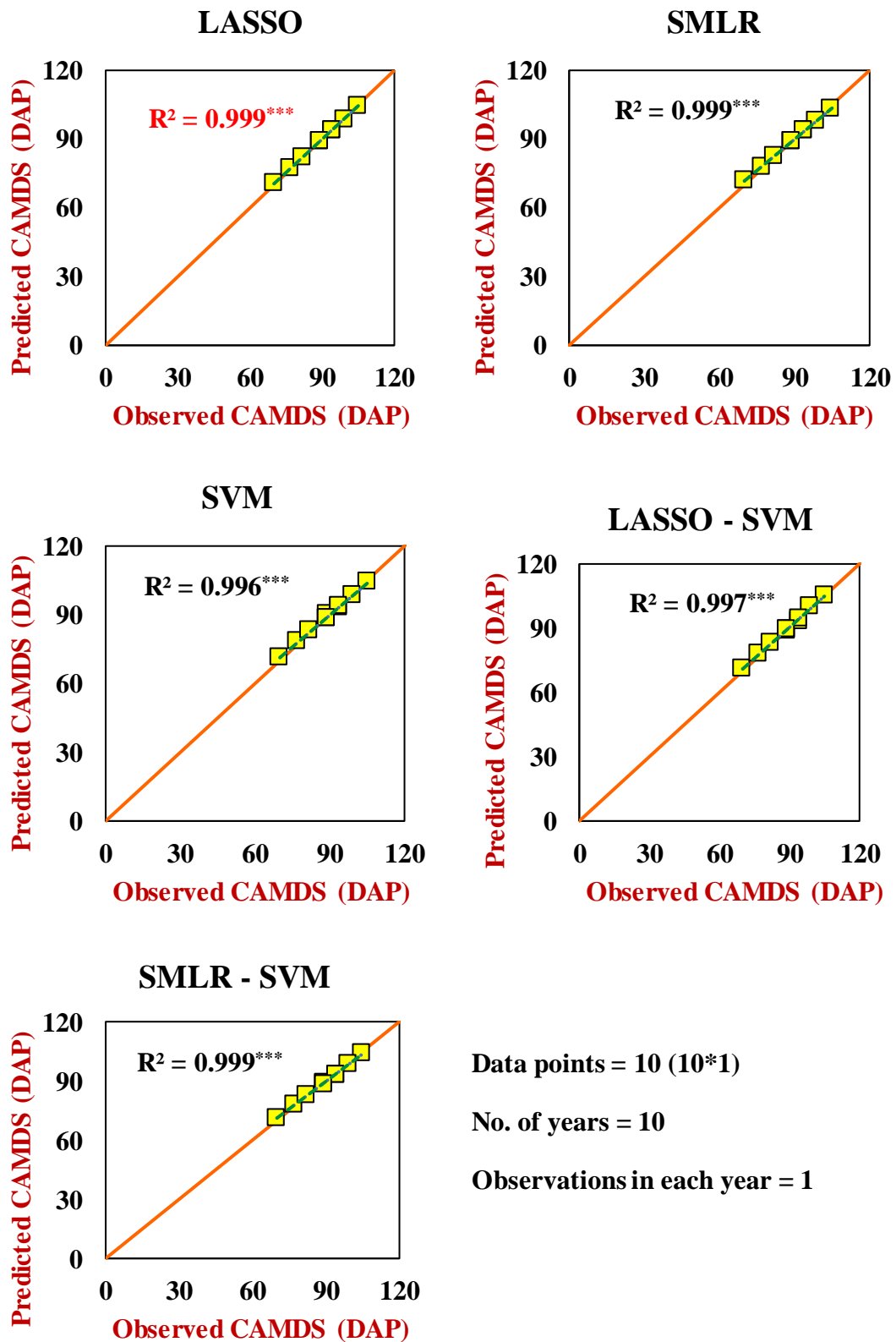


Fig. 4.26 Calibration of Crop Age at Maximum Disease Appearance (CAMDS) for normal planting at Kalyani, DAP-Days After Planting, *** = $P < 0.001$

Crop Age at Maximum Disease Severity (CAMDS): Kalyani – Late Planting

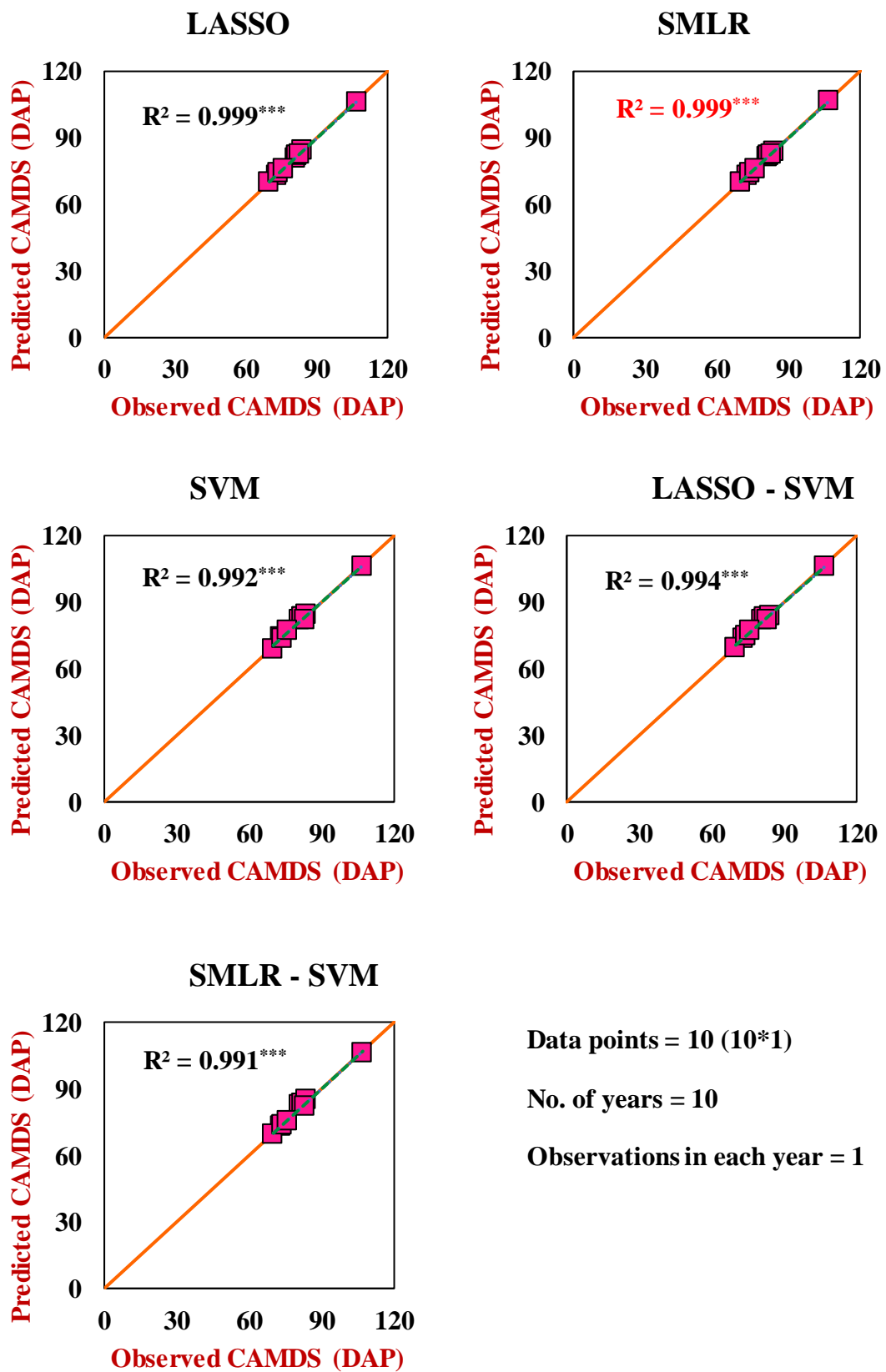


Fig. 4.27 Calibration of Crop Age at Maximum Disease Appearance (CAMDS) for Late planting at Kalyani, DAP-Days After Planting, *** = $P < 0.001$

Crop Age at Maximum Disease Severity (CAMDS): Kalyani – All Planting

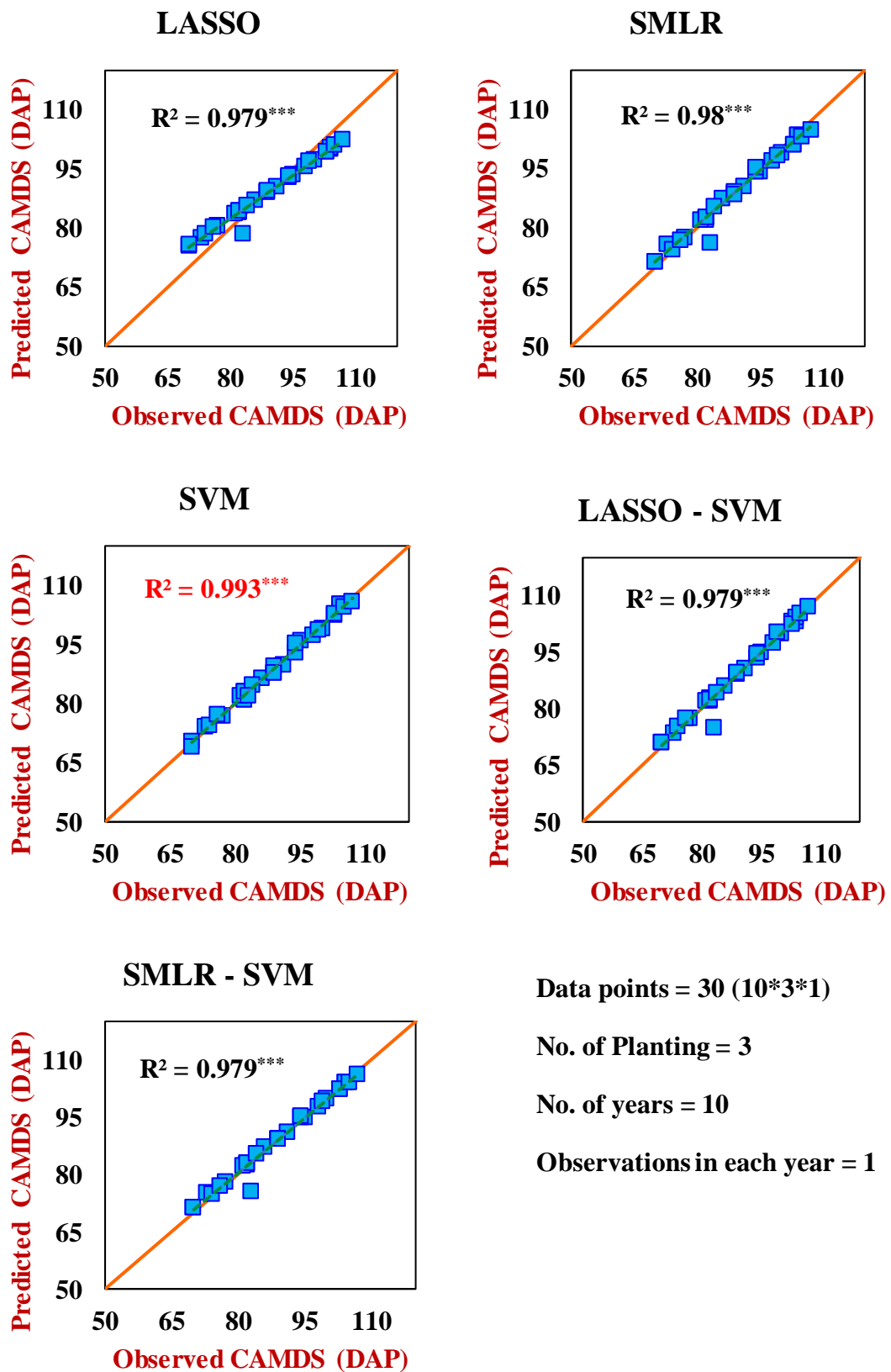


Fig. 4.28 Calibration of Crop Age at Maximum Disease Appearance (CAMDS) for all plantings at Kalyani, DAP-Days After Planting, *** = $P < 0.001$

5. DISCUSSION

To minimise the losses caused by diseases in agricultural production and reduce the indiscriminate use of pesticides it is essential to forecast the onset of disease. With access to timely forecast, farmers would be in the position to decide the management practices which need to be employed in advance (Kumar, 2017). Diseases of crop plants have strong relationship with weather and environmental conditions which have the potential to cause significant economic losses. Thus, it is essential to integrate weather information with the forecasting models to strengthen the decision-making system (Fenu and Mallocci, 2020). Further improvement in this integration can be made by the use of modelling and machine learning techniques (George *et al.*, 2019). Ahmed *et al.*, (2015) reported that the weather parameters significantly influence the development of late blight disease in potato crop.

5.1 Objective 1: To establish relationship between weather variables and potato late blight incidence.

To achieve this objective, long term weather data were collected from NASA powered web site SoDa _MERRA (Modern-Era Retrospective Analysis for Research and Applications version 2) for the locations Kalyani and Srinagar. Data collected on every 10 minutes were used calculate daily maximum and minimum temperature and morning and evening relative humidity, average wind speed, cumulative rainfall and solar radiations for each day. Daily weather data were collected during the crop growth period for the two locations Kalyani and Srinagar during the last 15 years (2006 to 2020). Data on disease parameters were obtained from AICRP Potato reports during the corresponding years (last 15 years - 2006 to 2020). Disease parameters selected for the study were Disease severity (DS) in %, crop age at first appearance of disease (CAFAD) in days after planting (DAP), crop age at maximum disease severity (CAMDS) in DAP. Further correlations of respective disease parameters with the weather variables were calculated.

5.1.1 Correlation of disease severity with weather parameters

Results showed that correlation of Disease severity of late blight with weather variables during the cropping season in Srinagar as well as Kalyani locations for early, normal and late planting conditions was not significant with any of the selected weather variables. This implies that change in single weather parameter in the prevailing weather conditions do not have much influence on severity of disease. However, the influence of the combination of weather parameters might play a significant effect on disease severity. It also implied that weather parameter might or might not have influence on infection and development of disease. It means once the disease is established it can multiply irrespective of the weather conditions within the

same crop field but for dissemination to other fields as well as survival of the pathogen weather conditions play a crucial role. Similar observations have been made by many researchers to predict the appearance and severity disease in crop plants. Raposo *et al.*, (1993) conducted a study in USA to evaluate the effectiveness of inclusion of weather forecasts into disease forecasting and they observed that weather forecasts contributed positively in disease forecasting however its contribution was smaller than expected. In a study conducted on the use of weather data for the prediction of disease epidemics Bourke (1970) reported that microclimatic conditions such as soil moisture regime, row spacing of plants, growth stage of the crop etc. influence the epidemics of disease irrespective of the prevailing weather conditions. Similarly in a study on prediction of Fusarium head blight of wheat based on weather series Shah *et al.*, (2019) reported that it was difficult to predict the epidemics of this disease using local weather data. Lehsten *et al.*, (2017) conducted a study on the occurrence of late blight of potato at Fennoscandia (Sweden) and reported that in initial stages of disease the relationship between weather parameters and disease incidence is weak or not much significant. While forecasting the grape downy mildew disease severity using machine learning, Chen *et al.*, (2020) reported that severity of the downy mildew disease in grapes is influenced more by the date of appearance of disease rather than climatic factors. Visker *et al.*, (2003) conducted a study on 5 different varieties of potato and found that age of plant and position of the leaf on plant has significant effect on providing resistance to the plant against potato late blight. Leaves at the apex were found to show more resistance against the disease as compared to leaves at the base regardless of the growing environment and variety. Each new leaf had a marginally increased resistance to late blight compared to the one that preceded it; however, the plant age did not show much resistance effect. Generally older plants were more resistant than younger plants however it has been observed that young plants are more susceptible, intermediate aged plants were resistant and old age plants were again susceptible to disease. Overall conclusion of their study was that older plants with a greater proportion of these more resistant leaves have a greater resistance. Similarly, early planted crops can completely escape from blight (Arora *et al.*, 1999). According to Awasthi and Kolte (1990) Susceptible growth stage of crop and favourable weather conditions must coincide for the infection and development of disease. Climate change also influence the severity of late blight of potato on global scale Sparks *et al.*, (2014) observed that patterns of crop disease severity are likely to vary as a result of climate change.

Furthermore, accurate measurement of environmental parameters and disease progression is required in order to relate disease development to weather conditions. With the development of new sensor technology, sites near diseased plants may now be measured for meteorological variables more precisely and accurately (Krause and Massie, 1975). Hence, we can conclude

that the probable reasons for obtaining non-significant correlation of disease severity of late blight with some of the weather parameters chosen for the research work could be that despite the favourable weather conditions disease was not reported due to unsuitable microclimatic conditions prevailing in the crop field. The susceptible stage of crop and favourable weather conditions would not have coincided and plant would have been resistant enough to fight the pathogen. One of the reasons for poor correlation could be non-occurrence of disease for Kalyani location as disease did not appear for 6 years in that location. The results obtained in our work doesn't validate insignificant relationship between weather parameters and disease however, the reasons could be one of those mentioned above which tried to justify the findings of our research work.

5.1.2 Correlation of CAFAD (crop age at first appearance of disease) and CAMDS (crop age at maximum disease severity) with weather parameters

Correlation of CAFAD and CAMDS with weather parameters during the cropping season in Srinagar under early planting condition was found to be positive with maximum temperature (0.741**), minimum temperature (0.746***), and solar radiation (0.711**) and negatively with RH II (-0.64**) and did not correlate significantly with other parameters. For normal planting it correlated positively with minimum temperature (0.715**), maximum temperature (0.699**) and solar radiation (0.585*) and negatively with evening relative humidity (-0.52*). For late planting CAFAD correlated positively with rainfall (0.56*).

Correlation of CAFAD and CAMDS with weather variables during the cropping season in Kalyani for early planting correlated positively with maximum temperature (0.7**) and solar radiation (0.53*) and negatively with morning RH (-0.705**) and evening RH (-0.697**) and did not correlate significantly with other parameters. For normal planting it correlated significantly with maximum temperature (0.70**), and solar radiation (0.57*) and negatively with morning RH (-0.766***) and evening RH (-0.751***). For late planting CAFAD and CAMDS correlated positively with rainfall (0.56*). This shows that if prevailing maximum and minimum temperature would be high and solar radiations incidence on earth surface would be high then disease will appear late and crop age at first appearance of disease will be more. However, if morning and evening relative humidity will be high then disease will appear early and crop age at first appearance of disease will be less. The results obtained in this study are justified by the results observed by Singh and Bhat (2004), they have reported that cool and cloudy conditions are favorable for late blight disease incidence. Arora *et al.*, (2012) revealing that RH of greater

than 85% and temperature varying from 7.2 to 26.6°C led to early appearance of disease thereby shorter CAFAD and CAMDS. Bhattacharyya *et al.*, (1983) reported that disease would appear early if hourly temperature varied from 10-20 °C and relative humidity of 80% or more for constant 18 hours for two successive days. The growth of disease-causing organisms in the field is delayed or stopped at high temperature (above 30°C) Agrios (2005), but this does not kill the pathogen, thus this observation supports our findings that high temperature conditions delay disease appearance. Similarly, while conducting research for discriminating late blight affected and healthy potato plants, Dutta *et al.*, (2014) observed that high temperatures and high humidity were conducive to disease outbreak and also observed that the weather conditions such as temperature in the range of 12.8 to 21.7°C, RH varying from 65% to 98%, rainfall 5.6-6.3mm etc are suitable for disease infestation. Hence, we can conclude that high temperature and higher insolation will prevent disease development and higher relative humidity and rainfall will favour disease development. When plant gets infected with disease its progression is very rapid hence, if disease symptoms are shown early (less CAFAD) then maximum disease severity is also achieved early (less CAMDS).

5.2 Objective 2: To develop and validate the weather-based forewarning model on incidence of late blight in potato.

To achieve this objective weather indices were developed along with the output parameters and the data set were divided into training and testing sets using random distribution approach. Out of the total 15 years data, 10 years data were used for development of the models and remaining 5 years data were used for validation of the developed models. Techniques utilised for development of models were - Support Vector Machine (SVM), Least Absolute Shrinkage and Selection Operator (LASSO), Stepwise Multiple Regression model (SMLR) and two hybrid techniques LASSO-SVM and SMLR-SVM. The developed models were evaluated using coefficient of determination, Root Mean Square Error (RMSE), normalized Root Mean Square Error (nRMSE) and Mean Absolute Percentage Error (MAPE).

5.2.1 Prediction of disease severity, CAFAD (crop age at first appearance of disease) and CAMDS (crop age at maximum disease severity) using LASSO, SVM, SMLR, LASSO-SVM and SMLR-SVM

The results obtained after evaluation of different models are discussed here.

5.2.1(a) Prediction of disease severity under different planting conditions for both the locations

For prediction of disease severity of all plantings (pooled together) at Srinagar location LASSO-SVM (nRMSE = 0.221) performed the best. For prediction of disease severity (DS) for early planting condition at Srinagar SMLR-SVM (nRMSE =0.078) performed the best, under normal planting conditions LASSO-SVM (nRMSE =0.186) performed better and under late planting condition LASSO-SVM (nRMSE =0.174) performed the best.

For prediction of disease severity of all plantings (pooled together) at Kalyani location SVM (nRMSE =0.344) performed the best. For prediction of disease severity (DS) for early planting condition at Kalyani LASSO (nRMSE = 0.269) performed the best, under normal planting conditions LASSO (nRMSE = 0.665) performed better and under late planting condition SMLR (nRMSE =0.373) performed the best.

5.2.1(b) Prediction of CAFAD (crop age at first appearance of disease) under different planting conditions for both the locations

For prediction of crop age at first appearance of disease (CAFAD) of all plantings (pooled together) at Srinagar SMLR-SVM (nRMSE = 0.243) performed the best. For prediction CAFAD under early planting condition SMLR-SVM (nRMSE = 0.321) performed the best, under normal planting conditions LASSO (nRMSE = 0.079) performed the best and under late planting conditions LASSO-SVM (nRMSE = 0.102) performed the best.

For prediction of CAFAD of all plantings (pooled together) at Kalyani SMLR (nRMSE =0.079) performed the best. For prediction of crop age at first appearance of disease (CAFAD) under early planting conditions at Kalyani SMLR (nRMSE =0.032) performed the best, under normal planting conditions SMLR (nRMSE =0.069) performed the best and under late planting conditions SVM (nRMSE =0.060) performed the best.

5.2.1(c) Prediction of CAMDS (crop age at maximum disease severity) under different planting conditions for both the locations

For prediction of crop age at maximum disease incidence (CAMDS) for all plantings (pooled together) at Srinagar SMLR (nRMSE =0.270) performed the best. For prediction of crop age at maximum disease incidence (CAMDS) performed the best under early planting condition LASSO-SVM (nRMSE =0.211) and also under normal planting conditions LASSO-SVM (nRMSE =0.174), however, LASSO performed the best under late planting conditions (nRMSE =0.033).

For prediction of crop age at maximum disease incidence (CAMDS) for all plantings (pooled together) at Kalyani LASSO-SVM (nRMSE =0.01) and SMLR-SVM (nRMSE =0.01) performed the best. LASSO performed the best under early planting condition (nRMSE

=0.005), normal planting conditions (RMSE =0.003) and under late planting conditions (nRMSE =0.002).

Over all we can conclude that for Srinagar location LASSO-SVM performed well in predicting Disease Severity and crop age at maximum disease severity (CAMDS) whereas SMLR-SVM performed well for forecasting crop age at first appearance of disease (CAFAD). For Kalyani performance of LASSO is found satisfactory for forecasting disease severity and CAMDS whereas for SMLR performed well for CAFAD

5.2.2 LASSO-SVM and SMLR-SVM

Hybrid approach were used in this study, in which variables selected by LASSO and SMLR were used as input variables for classification or regression by SVM. It is a novel approach and is less utilized in agricultural field. In our research work hybrid models (LASSO-SVM and SMLR-SVM) performed better than SVM, LASSO and SMLR for prediction of disease severity, CAFAD and CAMDS at Srinagar location. However, the value of nRMSE for these models was also high but was lower than other models considered in this study. Some of the research works where hybrid approach is utilized are discussed here, but not much of work is done in agriculture. A study was conducted by Goo *et al.*, (2016) for improving the prediction efficiency of the models and they utilized feature selection ability of LASSO for selection of variables along with data mining techniques such as SVM and CART. The results of this study showed that prediction accuracy of LASSO-SVM model was higher than other models. In a study for prediction of Solar flare, Benvenuto *et al.*, (2018) utilized both supervised and unsupervised techniques- LASSO for feature selection and fuzzy clustering for classification purpose. The results of their study had shown that hybrid approaches were more efficient in prediction. Huang *et al.*, (2020) had proposed a method for classification of cervical biopsy using feature selection ability of LASSO to get the average optimization time and ensemble learning- SVM for classification purpose. After evaluation of the performance, it was found that accuracy of hybrid method was higher. Ali *et al.*, (2022) Conducted a study in which LASSO and ridge regression were utilised for selecting features and classification algorithms such as k-NN was used. The results showed that hybrid approach produced better results for predicting survival of Hepatocellular carcinoma. In prediction of diseases noise reduction using hybrid approach Bhatia *et al.*, (2022) reported that hybrid models performed better than individual methods. In an experimental study on sugar beet Rumpf *et al.*, (2010) reported that SVM showed higher accuracy in early detection and classification of diseases. Study conducted by Gu *et al.*, (2020) for investigating the difference in cortical signal characteristics of left and right foot movements, used SMLR-SVM approach for feature selection and classification. Results gave higher accuracy with SMLR-SVM in discriminating between left and right foot movement

is high. Above mentioned works have shown the efficacy of hybrid models for forecasting purpose. Less works related to hybrid models are reported from agriculture sector. Hence more such works could be done to exploit the prediction potential of hybrid models in characterising the disease prediction in agriculture.

5.2.3 Stepwise Multiple Linear Regression (SMLR)

Stepwise Multiple Linear Regression (SMLR) is a regression technique which is used by many researchers for development of weather-based models for predicting appearance and severity of different diseases. In this study SMLR performed well in predicting Disease severity and CAFAD at Kalyani location. Naqvi *et al.* (2016) developed a forecasting model for bacterial leaf blight of rice based on in season dataset available for intensity of disease and climatic variables using SMLR technique and found it to be giving satisfactory predictions. While predicting groundnut rust (*Puccinia arachidis*) incidence, Narayana *et al.* (2006) found SMLR to perform well to determine the most important variables responsible for the disease. During estimation of disease severity of brown spot of rice Liu *et al.*, (2007) revealed that disease severity could be estimated efficiently using stepwise multiple linear regression approach. In order to explore potential of hyperspectral measurements taken aerially for developing an in-season system to predict yield in maize crop, Uno *et al.*, (2005) utilized statistical and artificial neural network approaches and concluded that SMLR to be efficient in seizing intricate association between crop yield and reflectance value. SMLR approach was used for identification of biological as well as meteorological parameters for predictions severity of leaf rust disease in wheat (Burleigh *et al.*, 1972) and was observed to be well correlated well with the disease severity. Equations which used inoculum as one of the variables had higher accuracy in comparison to those equations which did not use inoculum as a variable. A forecasting model for potato leaf roll virus based on SMLR was developed by Ali *et al.*, (2022) using on meteorological parameters for Faisalabad, Pakistan. Performance of the model was evaluated using coefficient of determination and root mean square error. Based on this, they concluded that model with SMLR approach, predicted potato leaf roll virus disease precisely. They also concluded that if primary source of inoculum was also used as one of the independent variables, then the errors in prediction reduced significantly and accuracy of models also increased. In natural conditions it is difficult to control the amount of inoculum and efficiency of infection hence this could be one of the reasons for inaccurate predictions.

Similar to our approach of using SMLR in late blight disease forecasting, a forecasting model for bacterial blight disease in cotton for Surat was developed by Sharma *et al.*, (2008). For this purpose they correlated the weather parameters and disease parameters and used SMLR approach for the development of model and were successful in predicting the intensity of disease

one week before the actual and hence helped in management of the disease to a great extent. De Wolf *et al.*, (2003) conducted a study for development of models for assessment of risk associated with fusarium head blight disease of wheat. They used SMLR and reported that various combinations of weather parameters such as temperature, Relative humidity and rainfall seven days preceding the anthesis to be potential variables to predict the disease. In order to develop a forecasting model for collar rot disease of betel vines in west Bengal Garain *et al.*, (2021), determined the effect of weather parameters, soil temperature and moisture on development of this disease. For this purpose, they utilised weather data obtained from regional observatory and multiple regression approach (MRA) and binary logistic model. However, the accuracy of binary logistic model was higher than multiple regression but the later was found satisfactory. MRA was utilized by Krause and Massie, (1975) to correlate the rate of disease proliferation with environmental factors and characterized the progression of disease outbreaks over time and forecasted the severity of the disease at a specific moment. Many researchers have developed prediction models using SMLR technique which was found to be accurate in predicting the parameters selected for the respective study.

5.2.4 Least Absolute Shrinkage and Selection Operator (LASSO)

Least Absolute Shrinkage and Selection Operator (LASSO) is utilized for development of prediction models by a large number of researchers. In our work LASSO has performed well for predicting CAMDS and disease severity at Kalyani location. Dalla Lana *et al.*, (2021) utilized LASSO regression to quantify the risk of natural adulteration of maize grain with deoxynivalenol and found its performance satisfactory. Even while predicting cleavage efficiency of RNA, Ueno *et al.*, (2021) found that LASSO performed satisfactory in prediction of efficiency, in both exogenous as well as endogenous genes. While comparing different machine learning and regression approaches in forecasting the epidemics of *Alternaria* blight in mustard Singh *et al.*, (2022) reported that LASSO performed satisfactorily out of all other selected approaches like ANN, ENET and ridge regression. In study on forecasting yield of crop based on weather indices Singh *et al.*, (2019), used LASSO and SMLR for selection of weather variables and reported that MSE and RMSE of LASSO was better. In order to predict wheat yield, Kumar *et al.*, (2019), evaluated the performance of different models and concluded that LASSO regression performed the best. In an Investigation on ensemble learning based approach for forecasting of global horizontal radiations Jiang *et al.*, (2017) utilised LASSO for feature selection. From their study they concluded that LASSO performed well at some of their selected sites. Effectiveness of various methods of regression in forecasting grape production was assessed by Oliveira *et al.*, (2018). From their findings they concluded that LASSO performed well in forecasting grape yield. Similarly, Chen *et al.*, (2020) conducted research for predicting the incidence and severity of downy mildew disease in Bordeaux region using machine learning

algorithms and they have reported that performance of LASSO was found to be satisfactory. In literature, we can find that LASSO to be extensively utilized for prediction of yield of different crops however less studies have explored its utilization in disease forecasting to predict disease appearance and severity.

Forecasting the disease epidemics is a challenging task due to unavailability of data, lack of proper surveillance of disease as well as changes in behavioural pattern of pathogen. To derive accurate forecast from the models it is necessary to overcome these challenges (Moran *et al.*, 2016). Krause and Massie, (1975) stated that the availability of reliable macro- and micro-climate forecasting systems is critical factor in deciding how effectively the disease forecasting systems will function. Additionally, it is difficult and little understood how macroclimate and microclimate relate to one another. As we have discussed earlier that micro-climate plays an important role in appearance and severity of disease hence the weather information utilised for prediction purpose must be of the micro-climate or should be taken from space closer to plants. The data on disease parameters must be taken continuously and proper surveillance of crop fields and continuous recording of data will help in reducing errors during prediction. Forecasting systems will benefit substantially from solutions to the aforementioned issues. According to Juroszek and Tiedemann (2011) occurrence, prevalence, and severity of disease in plants will undoubtedly vary as a result of climate change. The scheduling, selection, and effectiveness of chemical, physical, and biological control techniques as well as their application within integrated pest management (IPM) strategies will all be influenced by this. Pathogen responses to climate change will be difficult to anticipate precisely due to the variability and adaptability of pathogen populations. All these factors which limit the potential of disease forecasting models must be studied thoroughly and efforts should be taken to minimize all the sources of errors in disease forecasting systems so as to increase accuracy of the forecast and prevent the losses in yields due to pests and diseases.

6. SUMMARY AND CONCLUSION

Agriculture is one of the most important sectors of Indian economy. India is the second largest producer of fruits and vegetables. Out of these crops potato has its own importance being a staple food source for a large number of people across the country as well as world. Potato crop is affected by several pests and diseases and *Phytophthora infestans*, is the causal organism of late blight of potato, and it is the most serious pest attacking the crop. It causes significant losses in yield of crop both quantitatively as well as qualitatively. For the management of this disease farmers indiscriminately use higher doses of fungicides than recommended. This is hazardous to environment as well as consumers. To prevent this damage, timely forecast of incidence and severity of late blight is necessary which will help in adopting integrated management practices to prevent losses caused by the pathogen. Till date for forecasting disease in crop plants various models have been developed based on weather elements, these models have served its purpose to some extent but the major limitation of these models is region specificity and failure in disseminating the information to the farmers. Hence the present study was conducted to forewarn potato late blight based on weather elements using linear regression techniques- LASSO (Least absolute Shrinkage and Selection Operator), SMLR (Stepwise Multiple Linear Regression), SVM (Support Vector Machine) and two hybrid techniques LASSO-SVM and SMLR-SVM. Analysis was performed using R software for LASSO, SVM, LASSO-SVM and SMLR-SVM and SPSS software for SMLR. The locations selected for the research work were Srinagar and Kalyani which belong to different Agro-climatic regions- Western Himalayan Region and Lower Gangetic Plains respectively. Cultivar of potato selected for the study was Kufri Chandramukhi, which is a popular but late blight susceptible cultivar, grown in major potato cultivating belt of India. Disease parameters selected for the study were Disease severity (DS) in %, crop age at first appearance of disease (CAFAD) in days after planting (DAP), crop age at maximum disease severity (CAMDS) in DAP. Treatments were early planting, normal planting, late planting and all plantings (pooled data). Disease data for the work was obtained from AICRP potato reports from year 2006 to 2020 for both the locations and weather data was obtained from NASA powered website SoDA MERRA (Modern-Era Retrospective Analysis for Research and Applications version 2) during the crop growth period. The weather parameters selected were maximum temperature, minimum temperature, rainfall, morning relative humidity, evening relative humidity, wind speed and solar radiation. Using these weather variables 28 simple indices were calculated by taking summation of weather variables during the crop growth period and 28 weighted indices were calculated by taking sum product of weather variables and its correlation with disease parameter. These indices were used to run the models and the performance of different models was evaluated using R^2 , Root Mean Square

Error (RMSE), normalized Root Mean Square Error (nRMSE) and Mean Absolute Percentage Error (MAPE). Salient findings of the research work obtained are as follows:

- ❑ Correlation of Disease severity of late blight with weather variables during the cropping season in Srinagar as well as Kalyani for early, normal and late planting conditions was not found to be significant with weather parameters selected for the research work.
- ❑ Correlation of CAFAD and CAMDS with weather variables during the cropping season in Srinagar under early planting condition was found to be positive with maximum temperature (0.741**), minimum temperature (0.746***) and solar radiation (0.711**) and negative with evening relative humidity (-0.638**) and significant correlation was not found with the rest of the weather parameters.
- ❑ Under normal planting condition correlation of CAFAD and CAMDS was to be found positive with minimum temperature (0.715**), maximum temperature (0.699**) and solar radiation (0.585*) and negative with evening relative humidity (-0.520*) and significant correlation was not found in case of other weather parameters.
- ❑ Under late planting condition correlation of CAFAD and CAMDS was found to be positive only with rainfall (0.557*) and significant correlation was not found in case of other weather parameters.
- ❑ Correlation of CAFAD and CAMDS with weather variables during the cropping season in Kalyani under early planting condition was found to be positive with maximum temperature (0.696*) and solar radiation (0.525*) and negative with morning relative humidity (-0.705**) and evening relative humidity (-0.697**) and significant correlation was not found to be significant with other weather parameters.
- ❑ Under normal planting condition correlation of CAFAD and CAMDS was found to be positive with maximum temperature (0.704**) and solar radiation (0.565*) and negative with morning relative humidity (-0.766***) and evening relative humidity (-0.751***) and significant correlation was not found with the rest of the weather parameters.
- ❑ Under late planting condition correlation of CAFAD and CAMDS was found to be positive with rainfall (0.56*) and significant correlation was not found with the rest of the weather parameters.
- ❑ For prediction of disease severity (DS) under early planting condition at Srinagar, the model developed by SMLR-SVM technique (nRMSE = 0.078) was found to be the best.
- ❑ Under normal planting condition model developed by LASSO-SVM technique (nRMSE = 0.186) was found to be the best.

- ❑ Under late planting condition model developed by LASSO-SVM and SMLR-SVM techniques (nRMSE = 0.174) were found to be the best.
- ❑ For prediction of disease severity under all plantings (pooled together) at Srinagar location model developed by LASSO-SVM technique (nRMSE = 0.221) was found to perform better out of all the models developed.
- ❑ For prediction of disease severity (DS) under early planting condition at Kalyani, model developed by LASSO technique (nRMSE = 0.269) was found to perform better.
- ❑ Under normal planting condition model developed by LASSO technique (nRMSE = 0.665) was found to perform better.
- ❑ Under late planting condition model developed by SMLR technique (nRMSE = 0.373) was found to perform better.
- ❑ For prediction of disease severity of all plantings (pooled together) at Kalyani location, model developed by SVM technique (nRMSE = 0.344) was found to perform better.
- ❑ For prediction of crop age at first appearance of disease (CAFAD) under early planting condition model developed by SMLR-SVM technique (nRMSE = 0.321) was found to perform better.
- ❑ Under normal planting conditions model developed by LASSO technique (nRMSE = 0.079) was found to perform the best.
- ❑ Under late planting condition model developed by LASSO-SVM technique (nRMSE = 0.102) was found to perform the best.
- ❑ For prediction of crop age at first appearance of disease (CAFAD) of all plantings (pooled together) at Srinagar, the model developed by SMLR-SVM technique (nRMSE = 0.243) performed better.
- ❑ For prediction of crop age at first appearance of disease (CAFAD) under early planting conditions at Kalyani model developed by SMLR technique SMLR (nRMSE = 0.032) was the best.
- ❑ Under normal planting condition model developed by SMLR technique (nRMSE = 0.069) was found to be the best.
- ❑ Under late planting condition model developed by SVM technique (nRMSE = 0.060) was found to be the best.

- ❑ For prediction of crop age at first appearance of disease (CAFAD) of all plantings (pooled together) at Kalyani model developed by SVM technique (nRMSE = 0.077) was found to be the best.
- ❑ For prediction of crop age at maximum disease incidence (CAMDS) under early planting condition model developed by LASSO-SVM technique (nRMSE = 0.211) was found to perform better.
- ❑ Under normal planting conditions model developed by LASSO-SVM technique (nRMSE = 0.174) and SMLR (nRMSE = 0.19) performed better
- ❑ Under late planting condition model developed by LASSO technique (nRMSE = 0.033) was found to be the best.
- ❑ For prediction of crop age at maximum disease incidence (CAMDS) for all plantings (pooled together) at Srinagar model developed by SMLR technique SMLR (nRMSE = 0.270) performed better than other models tested in this study.
- ❑ For prediction of crop age at maximum disease incidence (CAMDS) under early planting condition at Kalyani, model developed by LASSO and SMLR technique (nRMSE = 0.005) was found to be the best.
- ❑ Under normal planting conditions model developed by LASSO technique (nRMSE = 0.003) was found to be the best.
- ❑ Under late planting conditions model developed by LASSO technique (nRMSE = 0.002) was found to be the best.
- ❑ For prediction of crop age at maximum disease incidence (CAMDS) for all plantings (pooled together) at Kalyani, model developed by SMLR-SVM technique (nRMSE = 0.010) was found to be the best.

Weather based forewarning models for potato late blight (*Phytophthora infestans* (Mont.) de Bary) incidence

ABSTRACT

Agrochemicals were released decades ago with the intention of increasing agricultural yields and safeguarding crop plants from pests. Every year, new chemical compounds and higher dosages of existing ones are employed to protect crops because, pests have adapted to and become resistant to chemicals. To protect our environment from these hazardous chemicals it is necessary to forewarn the incidence of pests and diseases so that integrated management practices can be adopted well before the incidence of disease. This is a data intensive process, hence, Machine learning, a branch of artificial intelligence, has got huge potential to resolve several barriers in the development of knowledge-based farming systems. Present study was aimed at developing weather-based forewarning models for late blight of potato for the locations Srinagar and Kalyani. The cultivar selected for the study was Kufri Chandramukhi which is a popular, late blight susceptible cultivar of potato grown in major potato growing regions in India. The weather parameters selected in this study were daily maximum temperature, minimum temperature, rainfall, morning relative humidity, evening relative humidity, wind speed and solar radiation, during the potato crop growing period from the year 2006 to 2020. Disease parameters selected for the study were Disease severity (DS) in %, crop age at first appearance of disease (CAFAD) in DAP (Days After Planting), crop age at maximum disease severity (CAMDS) in DAP. Variation of weather and disease parameters over the years was observed and correlation between disease and weather parameters was calculated. Furthermore, a total of 56 simple and weighted indices were developed using the above-mentioned weather parameters which served as inputs for development and validation of models. Regression techniques such as LASSO (Least absolute Shrinkage and Selection Operator), SMLR (Stepwise Multiple Linear Regression), SVM (Support Vector Machine) and two hybrid techniques LASSO-SVM and SMLR-SVM were employed to develop different models for early, normal, late and all planting (pooled data) conditions for both the locations (Srinagar and Kalyani). It was observed that potato late blight disease parameters CAFAD and CAMDS were positively correlated with maximum temperature, minimum temperature and solar radiation and negatively correlated with evening relative humidity in early and normal planting condition for both the locations, whereas under late planting conditions significant correlation was not

observed with any of the weather parameters. In this study Disease severity showed non-significant correlation with the selected weather parameters. Out of all the models developed, the performance of hybrid model like LASSO-SVM could predict the disease severity for Srinagar location with a nRMSE varied from 0.174 to 0.221. Model developed with LASSO could predict disease severity for location - Kalyani with a nRMSE between 0.269 to 0.665. LASSO-SVM (nRMSE varied from 0.01 to 0.211) also performed well for prediction of Crop age at first appearance of disease (CAFAD) and Crop age at maximum disease severity (CAMDS) at Srinagar and SMLR-SVM (nRMSE varied from 0.243 to 0.321) performed well for prediction of CAFAD at Srinagar. Whereas at Kalyani, LASSO (nRMSE varied from 0.002 to 0.005) performed well for prediction of CAMDS (crop age at maximum disease severity) and SMLR (nRMSE varied from 0.032 to 0.079) performed satisfactory for prediction of Crop age at first appearance of disease (CAFAD). It can be concluded that use of LASSO-SVM and LASSO can be extended to predict disease appearance and severity of potato late blight disease at Srinagar and Kalyani respectively. This approach can further be improved with other machine learning approaches, similarly it can be extended to develop similar models for other locations. The developed models can be used as Decision Support System for timely and easy dissemination of the information to the farming community.

आलू के पछेती झुलसा (फाइटोफथोरा इन्फेस्टैन्स (मोंट.) डे बैरी) रोग के लिए मौसम आधारित पूर्वाभास मॉडल

सार

कृषि की पैदावार बढ़ाने और फसलों के पौधों को कीटों से बचाने के इरादे से दशकों पहले कृषि रसायन जारी किए गए थे। फसलों की रक्षा के लिए हर साल नए रासायनिक यौगिकों और मौजूदा रसायनों की उच्च खुराक का उपयोग किया जाता है, क्योंकि कीट रसायनों के अनुकूल हो गए हैं और प्रतिरोधी बन गए हैं। हमारे पर्यावरण को इन खतरनाक रसायनों से बचाने के लिए कीटों और बीमारियों की घटनाओं के बारे में पूर्व चेतावनी देना आवश्यक है ताकि बीमारी की घटना से पहले एकीकृत प्रबंधन प्रथाओं को अपनाया जा सके। यह एक डेटा गहन प्रक्रिया है, इसलिए, मशीन लर्निंग जो कि कृत्रिम बुद्धिमत्ता की एक शाखा, में ज्ञान-आधारित कृषि प्रणालियों के विकास में कई बाधाओं को हल करने की बड़ी क्षमता है। वर्तमान अध्ययन का उद्देश्य श्रीनगर और कल्याणी स्थानों के लिए आलू के पछेती झुलसा रोग के लिए मौसम आधारित पूर्वानुमान मॉडल विकसित करना था। अध्ययन के लिए चुनी गई किस्म कुफरी चंद्रमुखी थी जो भारत में प्रमुख आलू उगाने वाले क्षेत्रों में उगाए जाने वाले आलू की एक लोकप्रिय, पछेती झुलसा अतिसंवेदनशील किस्म है। वर्ष २००६ से २०२० तक आलू की फसल उगाने की अवधि के दौरान अध्ययन के लिए चुने गए मौसम पैरामीटर दैनिक अधिकतम तापमान, न्यूनतम तापमान, वर्षा, सुबह की सापेक्ष आर्द्रता, शाम की सापेक्ष आर्द्रता, हवा की गति और सौर विकिरण थे। अध्ययन के लिए चुने गए रोग मानदंड थे रोग की गंभीरता (डीएस) प्रतिशत में, डीएपी में रोग की पहली उपस्थिति में फसल की उम्र (सीएफएडी) (रोपण के बाद के दिन), डीएपी में अधिकतम रोग गंभीरता पर फसल की उम्र (सीएमडीएस)। वर्ष दर वर्ष मौसम और रोग के मापदंडों में बदलाव देखा गया और रोग और मौसम के मापदंडों के बीच सहसंबंध की गणना की गई। इसके अलावा, उपर्युक्त मौसम मानकों का उपयोग करके कुल ५६ सरल और भारित सूचकांक विकसित किए गए थे जो मॉडलों के विकास और सत्यापन के लिए इनपुट के रूप में कार्य करते थे। रिग्रेशन तकनीक जैसे लासो (न्यूनतम पूर्ण संकोचन और चयन ऑपरेटर), एसएमएलआर (स्टेपवाइज मल्टीपल रेखिक रिग्रेशन), एसवीएम (सपोर्ट वेक्टर मशीन) और दो हाइब्रिड तकनीक लासो - एसवीएम और एसएमएलआर - एसवीएम को शुरूआती, सामान्य, देर से रोपण और सभी रोपण (जमा डेटा) की स्थिति के लिए दोनों स्थानों (श्रीनगर और कल्याणी) में विभिन्न मॉडल विकसित करने के लिए नियोजित किया गया था। यह देखा गया कि दोनों स्थानों के लिए प्रारंभिक और सामान्य रोपण स्थिति में, सीएफएडी और सीएमडीएस का अधिकतम तापमान, न्यूनतम तापमान और सौर विकिरण के साथ सकारात्मक संबंध था और शाम की सापेक्ष आर्द्रता के साथ नकारात्मक रूप से सहसंबद्ध थे। हालांकि, देर से रोपण की स्थिति में मौसम के किसी भी पैरामीटर के साथ महत्वपूर्ण संबंध नहीं देखा गया। इस अध्ययन में रोग की गंभीरता ने चयनित मौसम मापदंडों के साथ गैर-महत्वपूर्ण

सहसंबंध दिखाया। विकसित किए गए सभी मॉडलों में से, लासो - एसवीएम श्रीनगर स्थान के लिए रोग की गंभीरता का अनुमान ०.१७४ से ०.२२१ तक एनआरएमएसई भिन्नता के साथ लगा सकता है। लासो के साथ विकसित मॉडल कल्याणी के लिए एनआरएमएसई ०.२६९ से ०.६६५ के बीच तक रोग की गंभीरता का अनुमान लगा सकता है। लासो - एसवीएम (एनआरएमएसई ०.०१ से ०.२११ तक भिन्न) ने भी श्रीनगर में रोग की पहली उपस्थिति (सीएफएडी) और अधिकतम रोग गंभीरता (सीएमडीएस) पर फसल की उम्र की भविष्यवाणी के लिए अच्छा प्रदर्शन किया। एसएमएलआर-एसवीएम (एनआरएमएसई ०.२४३ से ०.३२१ तक भिन्न) ने श्रीनगर में सीएफएडी की भविष्यवाणी के लिए अच्छा प्रदर्शन किया। जबकि कल्याणी में, लासो (एनआरएमएसई ०.००२ से ०.००५ तक भिन्न) ने सीएमडीएस (अधिकतम रोग गंभीरता पर फसल की आयु) की भविष्यवाणी के लिए अच्छा प्रदर्शन किया और एसएमएलआर (एनआरएमएसई ०.०३२ से ०.०७९ तक भिन्न) ने रोग की पहली उपस्थिति में फसल की उम्र (सीएफएडी) की भविष्यवाणी के लिए संतोषजनक प्रदर्शन किया। यह निष्कर्ष निकाला जा सकता है कि लासो - एसवीएम और लासो के उपयोग को क्रमशः श्रीनगर और कल्याणी में आलू पछेती झुलसा रोग की बीमारी की उपस्थिति और गंभीरता की भविष्यवाणी करने के लिए विस्तारित किया जा सकता है। अन्य मशीन लर्निंग दृष्टिकोणों के साथ इस दृष्टिकोण को और बेहतर बनाया जा सकता है, और अन्य स्थानों के लिए समान मॉडल विकसित करने के लिए विस्तारित किया जा सकता है। विकसित मॉडलों का उपयोग निर्णय समर्थन प्रणाली के रूप में किया जा सकता है ताकि कृषक समुदाय को आसानी से समय पर जानकारी मिल सके ।

BIBLIOGRAPHY

- Agrios, G. N. (2005). *Plant pathology*. Elsevier.
- Ahmed, A. S., Obeas, Z. K., Abd Alhade, B., & Jaleel, R. A. (2022). Improving prediction of plant disease using k-efficient clustering and classification algorithms. *Int J Artif Intell*, 11(3), 939-948.
- Ahmed, N., Khan, M. A., Khan, N. A., & Ali, M. A. (2015). Prediction of potato late blight disease based upon environmental factors in Faisalabad. *Pakistan. J. Plant Pathol. Microbiol. S*, 3.
- Ali, M. A., Orban, R., Rajammal Ramasamy, R., Muthusamy, S., Subramani, S., Sekar, K., ... & Elminaam, D. S. A. (2022). A Novel Method for Survival Prediction of Hepatocellular Carcinoma Using Feature-Selection Techniques. *Applied Sciences*, 12(13), 6427.
- Ali, Y., Raza, A., Aatif, H. M., Ijaz, M., Ul-Allah, S., Rehman, S. U., ... & Moustafa, M. (2022). Regression Modeling Strategies to Predict and Manage Potato Leaf Roll Virus Disease Incidence and Its Vector. *Agriculture*, 12(4), 550.
- Amarjyothi, K., Kumar, D. P., & Saikrishnan, K. C. (2021). Identification and tracking of locust swarms by indian doppler weather radar. *IEEE Geoscience and Remote Sensing Letters*, 19, 1-4.
- Arora, R. K., Ahmad, I., & Singh, B. P. (2012). Forecasting late blight of potato in Punjab using JHULSACAST model. *Potato Journal*, 39(2).
- Arora, R. K., Sharma, K. K., & Bombawale, O. M. (1999). Management of potato late blight by changing planting date in north-western plain. *Journal of Mycology and Plant Pathology*, 29, 355-8.
- Awasthi, R. P., & Kolte, S. J. (1990). Effect of some epidemiological factors on occurrence and severity of Alternaria blight of rapeseed and mustard. In *Oil crops: proceedings of the three meetings held at Pantnagar and Hyderabad, India, 4-17 Jan. 1989: 1. The Brassica Subnetwork-II; 2. The Other Oil Crops Subnetwork-I; 3. The Oil Crops Network Steering Committee-I*. IDRC, Ottawa, ON, CA.
- Aweda, F. O., Adebayo, S., Samson, T. K., & Ojedokun, I. A. (2021). Modelling net radiative measurement of meteorological parameters using merra-2 data in sub-sahara african town. *Iranian (Iranica) Journal of Energy & Environment*, 12(2), 173-180.
- Azadbakht, M., Ashourloo, D., Aghighi, H., Radiom, S., & Alimohammadi, A. (2019). Wheat leaf rust detection at canopy scale under different LAI levels using machine learning techniques. *Computers and Electronics in Agriculture*, 156, 119-128.
- Babu, K. S., Vanama, V. S. K., Roy, A., & Prasad, P. R. (2017, September). Assessment of forest fire danger using automatic weather stations and MODIS TERRA satellite datasets for the state Madhya Pradesh, India. In *2017 International Conference on Advances in Computing, Communications and Informatics (ICACCI)* (pp. 1876-1881). IEEE.
- Bajracharya, M., & Sapkota, M. (2017). Profitability and productivity of potato (*Solanum tuberosum*) in Baglung district, Nepal. *Agriculture & Food Security*, 6(1), 1-8.
- Baker, K. M., Kirk, W. W., Stein, J. M., & Andresen, J. A. (2005). Climatic trends and potato late blight risk in the upper Great Lakes Region. *HortTechnology*, 15(3), 510-518.
- Barrett, C. B. (2010). Measuring food insecurity. *Science*, 327(5967), 825-828.
- Beaumont, A. (1947). The dependence on the weather of the dates of outbreak of potato blight epidemics. *Transactions of the British Mycological Society*, 31(1-2), 45-53.
- Benvenuto, F., Piana, M., Campi, C., & Massone, A. M. (2018). A hybrid supervised/unsupervised machine learning approach to solar flare prediction. *The Astrophysical Journal*, 853(1), 90.
- Bezemer, D., & Headey, D. (2008). Agriculture, development, and urban bias. *World development*, 36(8), 1342-1364.

- Bhardwaj, V., Srivastava, A. K., Sharma, S., Kumar, V., Kaushik, S. K., & Singh, B. P. (2013). Efficiency of different potato (*Solanum tuberosum* L) cross combinations in late blight resistance breeding. *International journal of Horticulture and agriculture*, 2, 63-69.
- Bhatia, A., Chug, A., & Singh, A. P. (2020, February). Hybrid SVM-LR classifier for powdery mildew disease prediction in tomato plant. In *2020 7th International conference on signal processing and integrated networks (SPIN)* (pp. 218-223). IEEE.
- Bhatia, A., Chug, A., Singh, A. P., Singh, R. P., & Singh, D. (2022). A Forecasting Technique for Powdery Mildew Disease Prediction in Tomato Plants. In *Proceedings of Second Doctoral Symposium on Computational Intelligence* (pp. 509-520). Springer, Singapore.
- Bhattacharya, S.K., Singh, D.S. and Khanna, R.N. (1982). Epidemiology and forecasting of *Phytophthora infestans* inciting potato late blight. In: *Phytophthora diseases of tropical cultivated plants*, Central Plantations Crops Research Institutes Kasaragod, Kerala.
- Bhattacharyya, S. K., SG, P., & DS, S. (1983). Efficacy of some fungicides in controlling late blight of potato in India.
- Bi, Q., Goodman, K. E., Kaminsky, J., & Lessler, J. (2019). What is machine learning? A primer for the epidemiologist. *American journal of epidemiology*, 188(12), 2222-2239.
- Binyamin, R., Ahmed, N., Ashraf, W., Li, Y., Ghani, M. U., Zeshan, M. A., ... & Vachova, P. (2022). Prediction of mungbean yellow mosaic virus disease using multiple regression models. *Journal of King Saud University-Science*, 102094.
- Borovskiy, K. V., Kuznetsova, M. A., Rogozhin, A. N., & Statsyuk, N. V. (2021, February). A new approach for designing decision support system used in the potato late blight and early blight management practice. In *IOP Conference Series: Earth and Environmental Science* (Vol. 663, No. 1, p. 012010). IOP Publishing.
- Bouma, E. (2007). Computer aids for plant protection, historical perspective and future developments. *EPPO bulletin*, 37(2), 247-254.
- Bourke, A. (1953). *Potato blight and the weather: a fresh approach*. Meteorological Service.
- Bourke, P. A. (1970). Use of weather information in the prediction of plant disease epiphytotics. *Annual Review of Phytopathology*, 8(1), 345-370.
- Bowes, G. (1993). Facing the inevitable: plants and increasing atmospheric CO₂. *Annual review of plant biology*, 44(1), 309-332.
- Branislava, L., Mihailović, D. T., Radovanović, S., Balaž, J., & Ćirišan, A. (2007). Input data representativeness problem in plant disease forecasting models. *QJ Hung Meteorol Serv*, 111, 199-208.
- Burleigh, J. R., Eversmeyer, M. G., & Roelfs, A. P. (1972). Development of linear equations for predicting wheat leaf rust. *Phytopathology*, 62, 947-953.
- Camire, M. E., Kubow, S., & Donnelly, D. J. (2009). Potatoes and human health. *Critical reviews in food science and nutrition*, 49(10), 823-840.
- Campbell, C. L., & Madden, L. V. (1990). *Introduction to plant disease epidemiology*. John Wiley & Sons.
- Charaya, M. U., Upadhyay, A., Bhati, H. P., & Kumar, A. (2021). 1. Plant Disease Forecasting: Past Practices to Emerging Technologies.
- Chattopadhyay, N., Samui, R. P., & Rathore, L. S. (2011). Strategies for minimizing crop loss due to pest and disease incidences by adoption of weather-based plant protection techniques. In *Challenges and opportunities in agrometeorology* (pp. 235-243). Springer, Berlin, Heidelberg.
- Chen, M., Brun, F., Raynal, M., & Makowski, D. (2020). Forecasting severe grape downy mildew attacks using machine learning. *PLoS One*, 15(3), e0230254.
- Chiang, K. S., Liu, H. I., & Bock, C. H. (2017). A discussion on disease severity index values. Part I: warning on inherent errors and suggestions to maximise accuracy. *Annals of Applied Biology*, 171(2), 139-154.
- Chlingaryan, A., Sukkarieh, S., & Whelan, B. (2018). Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review. *Computers and electronics in agriculture*, 151, 61-69.

- Coakley, S. M., Scherm, H., & Chakraborty, S. (1999). Climate change and plant disease management. *Annual review of phytopathology*, 37(1), 399-426.
- Cogato, A., Meggio, F., De Antoni Migliorati, M., & Marinello, F. (2019). Extreme weather events in agriculture: A systematic review. *Sustainability*, 11(9), 2547.
- Cooke, L. R., Schepers, H. T. A. M., Hermansen, A., Bain, R. A., Bradshaw, N. J., Ritchie, F., ... & Nielsen, B. J. (2011). Epidemiology and integrated control of potato late blight in Europe. *Potato research*, 54(2), 183-222.
- Dalla Lana, F., Madden, L. V., & Paul, P. A. (2021). Logistic Models Derived via LASSO Methods for Quantifying the Risk of Natural Contamination of Maize Grain with Deoxynivalenol. *Phytopathology*, 111(12), 2250-2267.
- De Vos, L., Leijnse, H., Overeem, A., & Uijlenhoet, R. (2017). The potential of urban rainfall monitoring with crowdsourced automatic weather stations in Amsterdam. *Hydrology and Earth System Sciences*, 21(2), 765-777.
- De Wolf, E. D., Madden, L. V., & Lipps, P. E. (2003). Risk assessment models for wheat Fusarium head blight epidemics based on within-season weather data. *Phytopathology*, 93(4), 428-435.
- Demissie, Y. T. (2019). Integrated potato (*solanum tuberosum* L.) late blight (*Phytophthora infestans*) disease management in Ethiopia. *American Journal of BioScience*, 7(6), 123-130.
- Devaux, A., Goffart, J. P., Petsakos, A., Kromann, P., Gatto, M., Okello, J., ... & Hareau, G. (2020). Global food security, contributions from sustainable potato agri-food systems. In *The potato crop* (pp. 3-35). Springer, Cham.
- Devaux, A., Kromann, P., & Ortiz, O. (2014). Potatoes for sustainable global food security. *Potato Research*, 57(3), 185-199.
- Diambra, L. A. (2011). Genome sequence and analysis of the tuber crop potato. *Nature*, 475.
- Dourado-Neto, D., Teruel, D. A., Reichardt, K., Nielsen, D. R., Frizzone, J. A., & Bacchi, O. S. (1998). Principles of crop modelling and simulation: II. The implications of the objective in model development. *Scientia Agricola*, 55, 51-57.
- Dowley, L. J., Grant, J., & Griffin, D. (2008). Yield losses caused by late blight (*Phytophthora infestans* (Mont.) de Bary) in potato crops in Ireland. *Irish Journal of Agricultural and Food Research*, 69-78.
- Du, M., Ren, X., Sun, Q., Wang, Y., & Zhang, R. (2012). Characterization of *Fusarium* spp. causing potato dry rot in China and susceptibility evaluation of Chinese potato germplasm to the pathogen. *Potato Research*, 55(2), 175-184.
- Dutta, S., Singh, S. K., & Panigrahy, S. (2014). Assessment of late blight induced diseased potato crops: A case study for West Bengal district using temporal AWiFS and MODIS data. *Journal of the Indian Society of Remote Sensing*, 42(2), 353-361.
- Ehetisham-ul-Haq, M., Rashid, A., Kamran, M., Idrees, M., Ali, S., Irum, A., ... & Siddique, F. (2017). Disease forecasting model for newly emerging bacterial seed and boll rot of cotton disease and its vector (*Dysdercus cingulatus*). *Archives of Phytopathology and Plant Protection*, 50(17-18), 885-899.
- Fabre, F., Plantegenest, M., & Yuen, J. (2007). Financial benefit of using crop protection decision rules over systematic spraying strategies. *Phytopathology*, 97(11), 1484-1490.
- Feleke, H. G. (2015). Assessing weather forecasting needs of smallholder farmers for climate change adaptation in the Central Rift Valley of Ethiopia. *Journal of Earth Science and Climate Change*, 6(10), 1-8.
- Fenu, G., & Mallocci, F. M. (2020, June). Artificial intelligence technique in crop disease forecasting: A case study on potato late blight prediction. In *International Conference on Intelligent Decision Technologies* (pp. 79-89). Springer, Singapore.
- Fenu, G., & Mallocci, F. M. (2021). Forecasting plant and crop disease: an explorative study on current algorithms. *Big Data and Cognitive Computing*, 5(1), 2.
- Fernandes, J. M. C., Pavan, W., & Sanhueza, R. M. (2011, September). SISALERT-A Generic Web-based Plant Disease Forecasting System. In *HAICTA* (pp. 225-233).

- Ferrante, A., & Mariani, L. (2018). Agronomic management for enhancing plant tolerance to abiotic stresses: High and low values of temperature, light intensity, and relative humidity. *Horticulturae*, 4(3), 21.
- Field, P. R., & Heymsfield, A. J. (2015). Importance of snow to global precipitation. *Geophysical Research Letters*, 42(21), 9512-9520.
- Forrer, H. R., Gujer, H. U., & Fried, P. M. (1993). PhytoPRE: a comprehensive information and decision support system for late blight in potatoes. *SP Report*.
- Førsund, E. (1983). Late Blight Forecasting in Norway 1957–1980 1. *EPPO Bulletin*, 13(2), 255-258.
- Fry, W. E. (2012). *Principles of plant disease management*. Academic Press.
- Fry, W. E., Apple, A. E., & Bruhn, J. A. (1983). Evaluation of potato late blight forecasts modified to incorporate host resistance and fungicide weathering. *Phytopathology*, 73(7), 1054-1059.
- Garain, P. K., Mondal, B., & Dutta, S. (2021). Influence of weather factors, soil temperature and moisture on collar rot disease of betel vine (*Piper betle* L.) under coastal saline zone of West Bengal. *Journal of Agrometeorology*, 23(4), 428-434.
- George, D. B., Taylor, W., Shaman, J., Rivers, C., Paul, B., O'Toole, T., ... & Reich, N. G. (2019). Technology to advance infectious disease forecasting for outbreak management. *Nature communications*, 10(1), 1-4.
- Gil, E., Gallart, M., Balsari, P., Marucco, P., Almajano, M. P., & Llop, J. (2015). Influence of wind velocity and wind direction on measurements of spray drift potential of boom sprayers using drift test bench. *Agricultural and forest Meteorology*, 202, 94-101.
- Glielmo, A., Husic, B. E., Rodriguez, A., Clementi, C., Noé, F., & Laio, A. (2021). Unsupervised learning methods for molecular simulation data. *Chemical Reviews*, 121(16), 9722-9758.
- Gokulnath, B. V., & Usha Devi, G. (2017). A survey on plant disease prediction using machine learning and deep learning techniques. *Inteligencia Artificial*, 22(63), 0-19.
- Goo, Y. J. J., Chi, D. J., & Shen, Z. D. (2016). Improving the prediction of going concern of Taiwanese listed companies using a hybrid of LASSO with data mining techniques. *SpringerPlus*, 5(1), 1-18.
- Goodwin, S. B., Cohen, B. A., & Fry, W. E. (1994). Panglobal distribution of a single clonal lineage of the Irish potato famine fungus. *Proceedings of the National Academy of Sciences*, 91(24), 11591-11595.
- Gu, L., Yu, Z., Ma, T., Wang, H., Li, Z., & Fan, H. (2020). EEG-based classification of lower limb motor imagery with brain network analysis. *Neuroscience*, 436, 93-109.
- Gu, Y. H., Yoo, S. J., Park, C. J., Kim, Y. H., Park, S. K., Kim, J. S., & Lim, J. H. (2016). BLITE-SVR: New forecasting model for late blight on potato using support-vector regression. *Computers and electronics in agriculture*, 130, 169-176.
- Gutsche, V. (1993). PROGEB—a model-aided forecasting service for pest management in cereals and potatoes 1. *EPPO Bulletin*, 23(4), 577-581.
- Han, J., Pei, J., & Tong, H. (2022). *Data mining: concepts and techniques*. Morgan kaufmann.
- Hannukkala, A. O., Kaukoranta, T., Lehtinen, A., & Rahkonen, A. (2007). Late-blight epidemics on potato in Finland, 1933–2002; increased and earlier occurrence of epidemics associated with climate change and lack of rotation. *Plant pathology*, 56(1), 167-176.
- Hansen, J. G., Andersson, B., & Hermansen, A. (1995). NEGFY-A system for scheduling chemical control of late blight in potatoes. *Phytophthora infestans*, 150, 201-208.
- Hardwick, N. V. (2006). Disease forecasting. In *The epidemiology of plant diseases* (pp. 239-267). Springer, Dordrecht.
- Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. *Weather and climate extremes*, 10, 4-10.

- Hatfield, J. L., Boote, K. J., Kimball, B. A., Ziska, L. H., Izaurralde, R. C., Ort, D., ... & Wolfe, D. (2011). Climate impacts on agriculture: implications for crop production. *Agronomy journal*, 103(2), 351-370.
- Hendrick, W. A., & Scholl, J. C. (1943). Technique in measuring joint relationship. The joint effects of temperature and precipitation on crop yield. *N. Carolina Agric. Exp. Stat. Tech. Bull*, 74.
- Hermansen, A. R. N. E., NæRSTAD, R. A. G. N. H. I. L. D., Glorvigen, B., Alm, H., & Sørensen, K. (2009). Forecasting potato late blight in Norway. *PPO-Spec. Rep*, 13, 301.
- Hijmans, R. J., Forbes, G. A., & Walker, T. S. (2000). Estimating the global severity of potato late blight with GIS-linked disease forecast models. *Plant pathology*, 49(6), 697-705
- Hsieh, J. Y., Huang, W., Yang, H. T., Lin, C. C., Fan, Y. C., & Chen, H. (2019). Building the rice blast disease prediction model based on machine learning and neural networks. *EasyChair: Manchester, UK*.
- Huang, P., Zhang, S., Li, M., Wang, J., Ma, C., Wang, B., & Lv, X. (2020). Classification of cervical biopsy images based on LASSO and EL-SVM. *IEEE Access*, 8, 24219-24228.
- Huang, Y., Zhang, J., Zhang, J., Yuan, L., Zhou, X., Xu, X., & Yang, G. (2022). Forecasting Alternaria Leaf Spot in Apple with Spatial-Temporal Meteorological and Mobile Internet-Based Disease Survey Data. *Agronomy*, 12(3), 679.
- Hyre, R. A. (1954). Progress in forecasting late blight of potato and tomato. *Plant Disease Reporter*, 38(4), 245-253.
- Jiang, H., Dong, Y., & Xiao, L. (2017). A multi-stage intelligent approach based on an ensemble of two-way interaction model for forecasting the global horizontal radiation of India. *Energy Conversion and Management*, 137, 142-154.
- Johnson, D. A., Alldredge, J. R., & Vakoch, D. L. (1996). Potato late blight forecasting models for the semiarid environment of south-central Washington. *Phytopathology*, 86(5), 480-484.
- Jones, G.D. (1998). *The Epidemiology of Plant Diseases*. 3rd Edition. Kluwer Academic Publishes London, 371- 388.
- Jørgensen, L. N., Secher, B. J., & Nielsen, G. C. (1996). Monitoring diseases of winter wheat on both a field and a national level in Denmark. *Crop Protection*, 15(4), 383-390.
- Juroszek, P., & Von Tiedemann, A. (2011). Potential strategies and future requirements for plant disease management under a changing climate. *Plant Pathology*, 60(1), 100-112.
- Kami, C., Lorrain, S., Hornitschek, P., & Fankhauser, C. (2010). Light-regulated plant growth and development. *Current topics in developmental biology*, 91, 29-66.
- Kaundal, R., Kapoor, A. S., & Raghava, G. P. (2006). Machine learning techniques in disease forecasting: a case study on rice blast prediction. *BMC bioinformatics*, 7(1), 1-16.
- Khalili, E., Kouchaki, S., Ramazi, S., & Ghanati, F. (2020). Machine learning techniques for soybean charcoal rot disease prediction. *Frontiers in plant science*, 11, 590529.
- Kirk, W. (2009). Potato late blight alert for the Midwest. *Field Crop Advisory Team Alert Current News Articles*.
- Kirk, W., Wharton, P., Hammerschmidt, R., Abu-el Samen, F., & Douches, D. (2013). Late blight. *Michigan state university extension bulletin E-2945*. East Lansing, MI. Available on: <http://www.potatodiseases.org/lateblight.html>.
- Kleinhenz, B., & Jörg, E. (1999). Validation of SIMPHYT I/II—a decision support system for Late Blight control in Germany. *PAV—Special Report*, 5, 115-128.
- Kleinhenz, B., Falke, K., Kakau, J., & Rossberg, D. (2007). SIMBLIGHT1—A new model to predict first occurrence of potato late blight. *EPPO bulletin*, 37(2), 339-343.
- Kobayashi, M., Yoshioka, M., Asai, S., Nomura, H., Kuchimura, K., Mori, H., ... & Yoshioka, H. (2012). StCDPK5 confers resistance to late blight pathogen but increases susceptibility to early blight pathogen in potato via reactive oxygen species burst. *New Phytologist*, 196(1), 223-237.
- Kranz, J. (1988). Measuring plant disease. In *Experimental techniques in plant disease epidemiology* (pp. 35-50). Springer, Berlin, Heidelberg.

- Krause, R. A., & Massie, L. B. (1975). Predictive systems: modern approaches to disease control. *Annual review of phytopathology*, 13(1), 31-47.
- Krause, R. A., Massie, L. B., & Hyre, R. A. (1975). Blitecast: a computerized forecast of potato late blight. *Plant Disease Reporter*, 59(2), 95-98.
- Kumar, K., Sridhar, J., Choudhary, V. K., Singh, H. K., Parameshwari, B., Kumar, K. S., ... & Sivalingam, P. N. (2021). New innovations and approaches for biotic stress management of crops. In *Innovations in Agriculture for a Self-Reliant India* (pp. 265-292). CRC Press.
- Kumar, M., Singh, J. K., Kumar, S., & Kumar, A. (2017). A comprehensive overview on black scurf of potato. *International Journal of Current Microbiology and Applied Sciences*, 6(10), 4981-4994.
- Kumar, S., Attri, S. D., & Singh, K. K. (2019). Comparison of Lasso and stepwise regression technique for wheat yield prediction. *Journal of Agrometeorology*, 21(2), 188-192.
- Kumar, V. (2017). Importance of weather prediction for Sustainable Agriculture in Bihar, India. *Archives of Agriculture and Environmental Science*.
- Lal, M., Sharma, S., Yadav, S. and Kumar, S., 2018. Management of late blight of potato. *Potato-From Incas to All Over the World*, pp.83-106.
- Landschoot, S., Vandecasteele, M., De Baets, B., Höfte, M., Audenaert, K., & Haesaert, G. (2017). Identification of *A. arborescens*, *A. grandis*, and *A. protenta* as new members of the European *Alternaria* population on potato. *Fungal biology*, 121(2), 172-188.
- Landschoot, S., Waegeman, W., Audenaert, K., Vandepitte, J., Haesaert, G., & De Baets, B. (2012). Toward a reliable evaluation of forecasting systems for plant diseases: a case study using *Fusarium* head blight of wheat. *Plant Disease*, 96(6), 889-896.
- Léchaudel, M., Génard, M., Lescourret, F., Urban, L., & Jannoyer, M. (2005). Modeling effects of weather and source–sink relationships on mango fruit growth. *Tree Physiology*, 25(5), 583-597.
- Lehsten, V., Wiik, L., Hannukkala, A., Andreasson, E., Chen, D., Ou, T., ... & Grenville-Briggs, L. (2017). Earlier occurrence and increased explanatory power of climate for the first incidence of potato late blight caused by *Phytophthora infestans* in Fennoscandia. *PLoS one*, 12(5), e0177580.
- Li, Y., Van Der Lee, T. A. J., Evenhuis, A., Van den Bosch, G. B. M., Van Bekkum, P. J., Förch, M. G., ... & Kessel, G. J. T. (2012). Population dynamics of *Phytophthora infestans* in the Netherlands reveals expansion and spread of dominant clonal lineages and virulence in sexual offspring. *G3: Genes/ Genomes/ Genetics*, 2(12), 1529-1540.
- Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8), 2674.
- Liu, Z. Y., Huang, J. F., Shi, J. J., Tao, R. X., Zhou, W., & Zhang, L. L. (2007). Characterizing and estimating rice brown spot disease severity using stepwise regression, principal component regression and partial least-square regression. *Journal of Zhejiang University Science B*, 8(10), 738-744.
- Lutaladio, N., & Castaldi, L. (2009). Potato: The hidden treasure. *Journal of food composition and analysis*, 22(6), 491-493.
- Mahapatra, S., Saha, P., & Das, S. (2018). Plant disease forecasting in the era of climate change: trends and applications. In *Recent approaches for management of plant diseases* (pp. 1-26). New Delhi: Indian Phytopathological Society.
- Mahesh, B. (2020). Machine learning algorithms-a review. *International Journal of Science and Research (IJSR).[Internet]*, 9, 381-386.
- Malik, A., & Kumar, R. (2021). AN OVERVIEW ON AGRICULTURE IN INDIA. *International Journal of Modern Agriculture*, 10(2), 2087-2095.
- Martin, A. D., Gary, A. S., Neil, C. G., Arthur, H. L., & Duane, P. (1994). Leaf blight diseases of potato. *North Dakota State University Agriculture and University Extension*.
- Martinelli, F., Scalenghe, R., Davino, S., Panno, S., Scuderi, G., Ruisi, P., ... & Dandekar, A. M. (2015). Advanced methods of plant disease detection. A review. *Agronomy for Sustainable Development*, 35(1), 1-25.

- Matson, M. E., Small, I. M., Fry, W. E., & Judelson, H. S. (2015). Metalaxyl resistance in *Phytophthora infestans*: Assessing role of RPA190 gene and diversity within clonal lineages. *Phytopathology*, *105*(12), 1594-1600.
- Miller, P. R., & O'Brien, M. (1952). Plant disease forecasting. *The Botanical Review*, *18*(8), 547-601.
- Mizubuti, E. S., & Fry, W. E. (1998). Temperature effects on developmental stages of isolates from three clonal lineages of *Phytophthora infestans*. *Phytopathology*, *88*(8), 837-843.
- Montgomery, D. C., Peck, E. A., & Vining, G. G. (2021). *Introduction to linear regression analysis*. John Wiley & Sons.
- Moran, K. R., Fairchild, G., Generous, N., Hickmann, K., Osthus, D., Priedhorsky, R., ... & Del Valle, S. Y. (2016). Epidemic forecasting is messier than weather forecasting: the role of human behavior and internet data streams in epidemic forecast. *The Journal of infectious diseases*, *214*(suppl_4), S404-S408.
- Morgan, M., Blank, C. and Seetan, R., 2021. Plant disease prediction using classification algorithms. *IAES International Journal of Artificial Intelligence*, *10*(1), p.257.
- Munir, M. (2018). Plant disease epidemiology: disease triangle and forecasting mechanisms in highlights. *Hosts Virus*, *5*(1), 7-11.
- Naqvi, S. A. H., Perveen, R., Umar, U. U. D., Rehman, A. U., Chohan, S., & Abbas, S. H. (2016). BACTERIAL LEAF BLIGHT OF RICE: A DISEASE FORECASTING MODEL BASED ON METEOROLOGICAL FACTORS IN MULTAN, PAKISTAN. *Journal of Agricultural Research (03681157)*, *54*(4).
- Narayana, L., Raut, S. P., & Gadre, U. A. (2006). Linear disease prediction model in groundnut rust epidemics. *Annals of Plant Protection Sciences*, *14*(1), 173-176.
- Narouei-Khandan, H. A., Shakya, S. K., Garrett, K. A., Goss, E. M., Dufault, N. S., Andrade-Piedra, J. L., ... & Bruggen, A. H. V. (2020). BLIGHTSIM: A new potato late blight model simulating the response of *phytophthora infestans* to diurnal temperature and humidity fluctuations in relation to climate change. *Pathogens*, *9*(8), 659.
- Niu, S., Luo, Y., Li, D., Cao, S., Xia, J., Li, J., & Smith, M. D. (2014). Plant growth and mortality under climatic extremes: an overview. *Environmental and Experimental Botany*, *98*, 13-19.
- Oliveira, R. C. D., Mendes-Moreira, J., & Ferreira, C. A. (2018, March). Agribusiness intelligence: Grape production forecast using data mining techniques. In *World Conference on Information Systems and Technologies* (pp. 3-8). Springer, Cham.
- Ortiz, O., & Mares, V. (2017). The historical, social, and economic importance of the potato crop. In *The Potato Genome* (pp. 1-10). Springer, Cham.
- Patz, J. A., Engelberg, D., & Last, J. (2000). The effects of changing weather on public health. *Annual review of public health*, *21*(1), 271-307.
- Prank, M., Kenaley, S. C., Bergstrom, G. C., Acevedo, M., & Mahowald, N. M. (2019). Climate change impacts the spread potential of wheat stem rust, a significant crop disease. *Environmental Research Letters*, *14*(12), 124053.
- Priestley, H. (2006). How to think like consumers and win. *Potato developments in a changing Europe*, 189-198.
- Py, C., de Langre, E., Moulia, B., & Hémon, P. (2005). Measurement of wind-induced motion of crop canopies from digital video images. *Agricultural and forest meteorology*, *130*(3-4), 223-236.
- Rana, R. K., & Anwer, M. D. (2018). Potato production scenario and analysis of its total factor productivity in India. *Indian Journal of Agricultural Sciences*, *88*(9), 1354-61.
- Raposo, R., Wilks, D. S., & Fry, W. E. (1993). Evaluation of potato late blight forecasts modified to include weather forecasts: a simulation analysis. *Phytopathology*, *83*(1), 103-108.
- Rinaldi, M., & He, Z. (2014). Decision support systems to manage irrigation in agriculture. *Advances in agronomy*, *123*, 229-279.
- Rivington, M., Matthews, K. B., Bellocchi, G., & Buchan, K. (2006). Evaluating uncertainty introduced to process-based simulation model estimates by alternative sources of meteorological data. *Agricultural Systems*, *88*(2-3), 451-471.

- Rothmann, L. A., & McLaren, N. W. (2018). Sclerotinia sclerotiorum disease prediction: A review and potential applications in South Africa. *South African Journal of Science*, 114(3-4), 1-9.
- Routray, A., Mohanty, U. C., Rizvi, S. R. H., Niyogi, D., Osuri, K. K., & Pradhan, D. (2010). Impact of Doppler weather radar data on numerical forecast of Indian monsoon depressions. *Quarterly Journal of the Royal Meteorological Society*, 136(652), 1836-1850.
- Rumpf, T., Mahlein, A. K., Steiner, U., Oerke, E. C., Dehne, H. W., & Plümer, L. (2010). Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. *Computers and electronics in agriculture*, 74(1), 91-99.
- Saha, M., Chakraborty, A., & Bhattacharya, K. (2020). Aerobiology, epidemiology and disease forecasting of false smut disease of rice in West Bengal, India. *Aerobiologia*, 36(2), 299-304.
- Sannakki, S., Rajpurohit, V. S., Sumira, F., & Venkatesh, H. (2013, July). A neural network approach for disease forecasting in grapes using weather parameters. In *2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT)* (pp. 1-5). IEEE.
- Sarker, I. H. (2021). Machine learning: Algorithms, real-world applications and research directions. *SN Computer Science*, 2(3), 1-21.
- Schepers, H. T. A. M. (1995). ProPhy: a computerized expert system for control of late blight in potatoes in the Netherlands. In *Proceedings XIII International Plant Protection Congress* (Vol. 48).
- Scholthof, K. B. G. (2007). The disease triangle: pathogens, the environment and society. *Nature Reviews Microbiology*, 5(2), 152-156.
- Scott, G. J., Petsakos, A., & Juarez, H. (2019). Climate change, food security, and future scenarios for potato production in India to 2030. *Food security*, 11(1), 43-56.
- Shah, D. A., Paul, P. A., De Wolf, E. D., & Madden, L. V. (2019). Predicting plant disease epidemics from functionally represented weather series. *Philosophical Transactions of the Royal Society B*, 374(1775), 20180273.
- Sharma, H. B., & KC, H. (2004, March). Participatory IDM research on potato late blight through farmers field school. In *Advances of horticulture research in Nepal. In Proceedings of the Fourth National Workshop on Horticulture*.
- Sharma, O. P., Patil, U. G., Patil, P. V., & Dhandapani, A. (2008). Prediction model for bacterial blight (*Xanthomonas axonopodis* pv. *malvacearum*) of cotton for central India. *Plant Disease Research*, 23(2), 55-59.
- Sharma, P., Singh, B. K., & Singh, R. P. (2018, July). Prediction of potato late blight disease based upon weather parameters using artificial neural network approach. In *2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT)* (pp. 1-13). IEEE.
- Shi, M. W., Wang, Q. L., Chen, X. L., Zhai, J. H., Deng, T. F., Kong, F. B., ... & Lang, J. F. (2009, September). Plant Disease Forecasting System Based on Datacollection. In *2009 International Conference on Management and Service Science* (pp. 1-4). IEEE.
- Shtienberg, D. (2013). Will decision-support systems be widely used for the management of plant diseases? *Annual review of phytopathology*, 51, 1-16.
- Singh, B. P., & Narayana Bhat, M. (2004). Emerging trends in the epidemiology of late blight of potato. *Annual Review of Plant Pathology* (Vol. 2), 2, 43-83.
- Singh, B. P., & Sharma, S. (2013). Forecasting of potato late blight. *International Journal of Innovative Horticulture*, 2(1), 1-11.
- Singh, B. P., Ahmad, I., Sharma, V. C., & Shekhawat, G. S. (2000). Jhulsacast: a computerized forecast of potato late blight in western Uttar Pradesh. *Journal of the Indian Potato Association*, 27(1-2), 25-34.
- Singh, B. P., Govindakrishnan, P. M., Ahmad, I., Rawat, S., Sharma, S., & Sreekumar, J. (2016). INDO-BLIGHTCAST—a model for forecasting late blight across agroecologies. *International Journal of Pest Management*, 62(4), 360-367.

- Singh, K. N., Singh, K. K., Sudheer, K., Sanjeev, P., & Bishal, G. (2019). Forecasting crop yield through weather indices through LASSO. *Indian Journal of Agricultural Sciences*, 89(3), 540-544.
- Singh, M., Setiya, P., Tewari, A. K., & Nain, A. S. (2022). Comparison of machine learning and regression approaches to forecasting Alternaria blight epidemic of Indian mustard.
- Singh, V. K., & Pundhir, V. S. (2013). Forecasting models for potato late blight management-a review. *Agricultural Reviews*, 34(2).
- Small, I. M., Joseph, L., & Fry, W. E. (2015). Development and implementation of the BlightPro decision support system for potato and tomato late blight management. *Computers and Electronics in Agriculture*, 115, 57-65.
- Smith, L. P. (1956). Potato blight forecasting by 90 per cent humidity criteria. *Plant Pathology*, 5(3), 83-87.
- Smith, L. P. (1956). Potato blight forecasting by 90 per cent humidity criteria. *Plant Pathology*, 5(3), 83-87.
- Smith, W. L., Bishop, W. P., Dvorak, V. F., Hayden, C. M., McElroy, J. H., Mosher, F. R., ... & Wark, D. Q. (1986). The meteorological satellite: overview of 25 years of operation. *Science*, 231(4737), 455-462.
- Smyth, G. K. (2002). Nonlinear regression. *Encyclopedia of environmetrics*, 3, 1405-1411.
- SOARE, E., & CHIURCIU, I. A. (2021). STUDY ON THE DYNAMICS OF POTATO PRODUCTION AND WORLDWIDE TRADING DURING THE PERIOD 2012-2019. *changes*, 21(4).
- Son, S. W., Kim, H. Y., Choi, G. J., Lim, H. K., Jang, K. S., Lee, S. O., ... & Kim, J. C. (2008). Bikaverin and fusaric acid from *Fusarium oxysporum* show antiomycete activity against *Phytophthora infestans*. *Journal of Applied Microbiology*, 104(3), 692-698.
- Sparks, A. H., Forbes, G. A., Hijmans, R. J., & Garrett, K. A. (2014). Climate change may have limited effect on global risk of potato late blight. *Global change biology*, 20(12), 3621-3631.
- Taylor, M. C., Hardwick, N. V., Bradshaw, N. J., & Hall, A. M. (2003). Relative performance of five forecasting schemes for potato late blight (*Phytophthora infestans*) I. Accuracy of infection warnings and reduction of unnecessary, theoretical, fungicide applications. *Crop Protection*, 22(2), 275-283.
- Tiwari, R. K., Bashyal, B. M., Shanmugam, V., Lal, M. K., Kumar, R., Sharma, S., ... & Aggarwal, R. (2021). Impact of *Fusarium* dry rot on physicochemical attributes of potato tubers during postharvest storage. *Postharvest Biology and Technology*, 181, 111638.
- TS, A., Das, B. K., Kumar, B., Kuttippurath, J., & Chakraborty, A. (2018). Analyses of the oceanic heat content during 1980–2014 and satellite-era cyclones over Bay of Bengal. *International Journal of Climatology*, 38(15), 5619-5632.
- Tsedaley, B. (2014). Late blight of potato (*Phytophthora infestans*) biology, economic importance and its management approaches. *Journal of Biology, Agriculture and Healthcare*, 4(25), 215-225.
- Ueno, D., Kawabe, H., Yamasaki, S., Demura, T., & Kato, K. (2021). Feature selection for RNA cleavage efficiency at specific sites using the LASSO regression model in *Arabidopsis thaliana*. *BMC bioinformatics*, 22(1), 1-17.
- Ullrich, J., & Schrödter, H. (1966). The problem of predicting the occurrence of potato late blight (*Phytophthora infestans*) and the possibility of its solution by a "negative prognosis". *Newsletter German. Plant Protection Service (Braunschweig)*, 18, 33-40.
- Uno, Y., Prasher, S. O., Lacroix, R., Goel, P. K., Karimi, Y., Viau, A., & Patel, R. M. (2005). Artificial neural networks to predict corn yield from Compact Airborne Spectrographic Imager data. *Computers and electronics in agriculture*, 47(2), 149-161.
- Ushadevi, G. (2020). A survey on plant disease prediction using machine learning and deep learning techniques. *Inteligencia Artificial*, 23(65), 136-154.

- Van Everdingen, E. (1926). Het verband tusschen de weersgesteldheid en de aardappelziekte (*Phytophthora infestans*). *Tijdschrift over plantenziekten*, 32(5), 129-139.
- Vicente-Serrano, S. M., Domínguez-Castro, F., Reig, F., Beguería, S., Tomas-Burguera, M., Latorre, B., ... & El Kenawy, A. (2022). A near real-time drought monitoring system for Spain using automatic weather station network. *Atmospheric Research*, 271, 106095.
- Visker, M. H. P. W., Keizer, L. C. P., Budding, D. J., Van Loon, L. C., Colon, L. T., & Struik, P. C. (2003). Leaf position prevails over plant age and leaf age in reflecting resistance to late blight in potato. *Phytopathology*, 93(6), 666-674.
- Wallin, J. R. (1962). Summary of recent progress in predicting late blight epidemics in United States and Canada. *American Potato Journal*, 39(8), 306-312.
- Wang, A., Zhang, W., & Wei, X. (2019). A review on weed detection using ground-based machine vision and image processing techniques. *Computers and electronics in agriculture*, 158, 226-240.
- Weisberg, S. (2005). *Applied linear regression* (Vol. 528). John Wiley & Sons.
- Wharton, P., Hammerschmidt, R., & Kirk, W. (2007). *Fusarium dry rot*. Michigan State University.