AN ABSTRACT OF THE THESIS OF

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Title: Developing Models to Predict Favorable Environments for Rice Blast

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Stella M. Coakley

Statistical analyses were used to develop predictive models of rice blast and to relate the favorability of environment to disease incidence and severity on different rice cultivars at five sites in Asia. The WINDOW PANE program was used to search for weather factors highly correlated with blast. Stepwise and r-square linear regression procedures were then applied to generate the predictive models at each site. Models developed at Icheon, South Korea included relative humidity and rainfall factors as the most important predictors of disease. Temperature, rainfall, wind speed, and relative humidity factors were components of models at Cavinti and the IRRI blast nursery in the Philippines. Rainfall, temperature, and solar radiation factors were important at Gunung Medan and Sitiung, Indonesia. Model validation was done to verify accuracy of models for predictions. Model predictions were

also used to determine the effects on blast of sowing time, nitrogen amount, and increase in temperature. Limitations of the models are discussed.

Path coefficient analysis was used to identify direct and indirect influences exerted by weather factors on blast. The largest direct influence on disease was exerted by humidity factors at Icheon; temperature, rainfall, and wind speed factors at Cavinti; temperature and humidity factors at IRRI; rainfall factors at Gunung Medan; and temperature factors at Sitiung. Although path coefficient values (Py) were estimated from the decomposition of correlation coefficients, factors that had a high correlation with disease parameters did not always give high Py.

Multivariate analysis was used to determine the effects of sowing times on proneness of tropical rice to blast. Cluster analysis of 24 hypothetical sowing months at Cavinti, the IRRI blast nursery, and Sitiung sites revealed three blast proneness groups. Principal component analysis showed that IR50 cultivar would be susceptible at Cavinti at any time of the year. Sowing C22 cultivar at Cavinti in Group I and III months would make it prone to panicle and leaf blast, respectively. At the IRRI blast nursery, leaf and panicle infections on IR50 would be probable only in Group I and II months. This trend was also observed for C22 at Sitiung, although some months in Group III at this site had moderate to high degree of proneness to leaf blast.

Developing Models to Predict Favorable Environments for Rice Blast

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... and, to the **Lord Almighty** whom this success rests.

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Developing Models to Predict Favorable Environments for Rice Blast

CHAPTER I
INTRODUCTION

Rice is a plant of antiquity and importance. The gathering of wild-growing rice preceded the beginning of agriculture in the humid tropics of Asia and some parts of the temperate regions. Known as the "grains of life", rice is considered the staple food in most parts of the world (FAO, 1966). About 90% of the world's rice is grown and consumed in Asia where more than half of the world's people live (Ward, 1985).

Increases in human population result in corresponding increases in rice consumption despite limited production areas. By the year 2020, the world's annual rice production would have to increase by 60% from 470 to 760 million tons inorder to maintain current nutritional levels (IRRI, 1993). Such a level of production is attainable if the components of the agroecosystem can operate at their optimum, i.e. ideal environment and edaphic conditions for crop growth, appropriate field and crop management, socially acceptable and environmentally feasible production schemes (Carroll et al., 1990; Conway, 1986). In the majority of rice-growing areas, yield loss due to disease is the most important factor that hampers production goals.

ECONOMIC IMPORTANCE OF RICE BLAST DISEASE

Disease outbreaks are one of the most important reasons why economic losses in rice are exacerbated in spite of intensified research efforts to reduce their occurrence. Among these diseases, rice blast caused by a heterothallic, unitunicate Pyrenomycete fungus, *Magnaporthe grisea* Herb. (Webster, 1980) (anamorph= *Pyricularia grisea* (Cooke) Sacc. (Rossman et al., 1990)), remains a particular threat because of its unpredictable outbreaks (Teng, 1993), its ability to cause damage at both the vegetative and panicle stages of growth (Ou, 1985; Teng et al., 1991), and its resilience to adverse environments (Parthasarathy and Ou, 1965). Blast is found to be extremely important in both lowland and upland rice ecosystems of temperate and tropical regions (Bhatt and Singh, 1992; Chaudhary and Vishwadhar, 1988; IRRI, 1989), and even in mangrove and swampy areas of Sierra Leone in Africa (Fomba, 1984).

Several epidemics of the disease have been recorded that caused tremendous losses in yield. Crill et al. (1982) reported that it is the only rice disease that has ever caused serious problems in Korea. In Japan, an epidemic in 1953 caused yield reduction of about 800,000 tons (Goto, 1965). In the Philippines, production losses of over 90% were estimated in two provinces during 1962 and 1963 (Villareal, 1979). In India, large scale epidemics were reported to cause losses of more than 65% in Madras state and in some peninsular regions (Padmanabhan, 1965). Although major epidemics have not been reported in other rice-growing areas of the world, production losses due to blast are known to occur on a regular basis (Teng, 1993).

Blast is perceived to be more of a problem in upland rice systems; it is, however, causing more loss in tonnage in lowland rice because of the larger production areas devoted to the latter (Teng, 1993). This is especially so in the sub-tropical and cool temperate rice areas of China, Korea, Japan, and Taiwan (Teng, 1993). Potential outbreaks in lowland fields are therefore important because the world's food security relies almost exclusively on these rice systems (Teng, 1993).

RICE BLAST EPIDEMIOLOGY IN RELATION TO THE PHYSICAL ENVIRONMENT

Epidemics of blast disease result from favorable interaction between components of the pathosystem. Given a compatible host-pathogen relationship, crop growth and disease severity rely primarily on the existing ambient and edaphic environmental conditions. As in most air-borne pathogens, the life cycle of *P. grisea* is a series of overlapping monocycles that make up a polycyclic process during the growing season (Kato, 1974; Kingsolver et al., 1984). Each stage in the monocycle is affected by weather conditions, either directly (El Refaei, 1977; Kato, 1974; Kato and Kozaka, 1974; Suzuki, 1975; Yoshino, 1972) or indirectly through plant predisposition (Beier et al., 1959; Gill and Bonman, 1988; Hashioka, 1965; Kahn and Libby, 1954), either immediately or with some time lag (Hashioka, 1965; Teng and Calvero, 1991).

Initial inoculum survival. The beginning of epidemics depends on the viability of initial inoculum. Blast conidia survive in plant residues, in living tissues, or in seeds (Jeyanandarajah and Seveviratne, 1991; Ou, 1985). Dissemination of *P. grisea* by air is considered the most important means of long-distance transport in triggering outbreaks. Once spores are air-borne, temperature and relative humidity influence survival. In temperate regions, blast conidia survive in low temperature regimes (Abe, 1935;

Ito and Kuribayashi, 1931). In tropical regions, high temperature during the dry season does not affect *P. grisea* spores because of their ability to withstand temperature beyond 50-60 C (Kapoor and Singh, 1977).

Effect of humidity on survival is not well documented, although some reports have shown that conidia remain viable for a year at 20% relative humidity (Hashioka, 1965). In cool temperate rice areas in Japan, conidia and hyphae may survive on nodes of culms of a rice plant for more than a year; under dry indoor conditions, survival may exceed 1,000 days. Whereas, viability is lost under moist conditions in soil or compost (Ito and Kuribayashi, 1931).

Liberation and dispersal. Several studies show that liberation of conidia over field and nursery plots have peaks during late night to early morning hours (Barksdale and Asai, 1961; Hashioka, 1965; Kato, 1974; Kato, 1976; Kingsolver et al., 1984; Ou et al., 1974; Suzuki, 1975). A study also demonstrated that release of conidia is possible even during noon time under controlled environments (personal communication, Henry Klein-Gebbinck, University of Alberta, Edmonton). Patterns of spore liberation are affected by several environmental factors. Among these factors, darkness, high relative humidity, wind speed above 3.4 m/s, and rainfall over 83 mm/day are most favorable for release (Hashioka, 1965; Kato, 1974; Kim, 1987; Kim and Kim, 1991; Kim and Yoshino, 1987; Kingsolver et al., 1984;

Nakamura, 1971; Ou et al., 1974; Suzuki, 1975). Temperature, on the other hand, has both direct and indirect effects on liberation due to its contribution to dew formation.

Kato (1974) reported that a mean temperature of 19 C triggers spore release but Ono and Suzuki (1959) believed that release is not temperature-dependent. Other studies have shown that water deposits from dew formation affect spore detachment from conidiophores. *In vivo*, conidia detach readily when water attaches to the junction between spores and conidiophores (El Refaei, 1977). Such a mode of liberation is observed even below the optimum microclimatic conditions if spores are mature (Yoshino, 1972). Another means of spore liberation is by strong winds and heavy rainfall. Both the immature and mature conidia are released by the shaking of infected leaves and panicles caused by wind velocities of over 3 or 4 m/s or rainfall of more than 83 mm/day (Hashioka, 1965; Kato, 1974; Kim, 1987; Kim and Kim, 1991; Kim and Yoshino, 1987; Nakamura, 1971; Ou et al., 1974; Suzuki, 1975).

Successful spore dispersal aided by wind and water (in the form of rainfall or irrigation) has a major impact on the potential of epidemics. Gradients of dispersion for blast conidia are influenced by dominant wind directions and speed (Kato, 1974; Suzuki, 1975). Both are found important in blast epidemics because of their direct effect on the pattern of spore distribution across crop canopies and across rice fields (Koizumi and Kato, 1991; Suzuki, 1975). A logical representation of a spore profile along the canopy is a skewed probability density function curve rotated 90 degrees clockwise. The asymptote or the maximum number of spores is observed a few centimeters above ground and tapers-off with increasing canopy height (Koizumi and Kato, 1991). Similarly, few spores are observed just above the canopy because of wind turbulence.

Splash dispersal is the most common form of dissemination by rain or irrigation water. Rainfall or irrigation either increases the build-up of infection due to increased splash dispersion, or, hinders infection due to washing-off of spores from infected leaves or from spore-laden air. In Korea (Kim and Kim, 1991) and Japan (Suzuki, 1975), the peak of spore dispersion is observed immediately after heavy rainfall. In some blast-prone tropical and sub-tropical areas where continuous rainfall is experienced, heavy downpour may reduce the chance of a disease outbreak (Bhatt and Chauhan, 1985; Padmanabhan et al., 1971; Surin et al., 1991; Tsai, 1986; Venkatarao and Muralidharan, 1982). This may be due to washing-off of spores from leaves or to deposition of air-borne spores from rain scrubbing. Kato (1974) and Suzuki (1975) reported, that although heavy rainfall causes a decrease in blast occurrence, its contribution to dispersion and to providing moisture for infection significantly influences subsequent epidemic development.

Infection. The infection process consists of three parts: conidial germination, appressorial formation, and penetration. Although these parts require host tissue, the success of completing one stage to the next is also influenced by leaf wetness period, temperature, relative humidity, and soil nutrients. Some simulation models include germination as an on-off function with the presence of free moisture on leaves or panicles as a driving parameter (Gunther, 1986; Tastra et al., 1987). At 18-38 C, spore germination starts within three hours after spore deposition if host tissues are wet (Kato, 1974). In *in vitro* studies, germination occurs 4-6 hours after deposition at 12 C; no germination occurs below 5 C (El Refaei, 1977). An increase in percent germination is also observed at an optimum temperature range of 20-25 C when spores are incubated in water. Spores that are subjected to dry periods prior to incubation in water have reduced viability (El Refaei, 1977; Kato, 1974; Suzuki, 1975).

Appressorial formation occurs 6 hours after spores are incubated in moist conditions. Studies have shown a variation in range of temperatures required for formation of appressoria (Ito and Kuribayashi, 1931; Kato, 1974; Rahnema, 1978; Suzuki, 1969; Yoshino, 1972). El Refaei (1977) examined appressorial formation *in vitro* along with varying relative humidity. He found that humidity has no direct relationship to appressorial formation, but a temperature range of 21-30 C is most favorable.

Penetration and colonization of *P. grisea* in host tissues are influenced by both environment and the genetic relationship between host and pathogen. An incompatible relationship can be expressed even under optimum environmental conditions for disease. With *P. grisea* infecting both leaves and panicles, there is some evidence to suggest that a cultivar could be susceptible to leaf infection but not to panicle infection or vice-versa (personal communication, Bienvenido Estrada, International Rice Research Institute (IRRI)). In most production systems, such incompatibility is broken down as new pathogen races occur among pathogen populations. The impact of environment on infection is obvious once incompatibility is overcome.

In general, rate of leaf colonization by the pathogen increases with increasing temperature up to 28 C (El Refaei, 1977; Kato, 1974; Veeraghavan, 1982) and may differ among pathogen races (Hashioka, 1965). The likelihood of panicle colonization, on the other hand, is dictated mostly by a minimum temperature below 21 C (Bhatt and Chauhan, 1985; Ishiguro and Hashimoto, 1988). Rainfall differentially affect the success of leaf and panicle infections apparently due to tissue orientation (Kato, 1974). Heavy rain deposits spores by impaction on panicles which are oriented vertically but it washes off conidia attached on horizontally-oriented leaf surfaces. Panicle infection, however, can occur with processes other than impaction which is the reason why a potential simulation model depicting panicle blast pathosystem should have stochastic processes to explain deposition (Ishiguro and Hashimoto, 1988, 1989).

Nitrogen fertilization and soil silica content have been shown to influence blast occurrence. Higher nitrogen increases susceptibility of rice to leaf and panicle infections (Beier et al., 1959; Paik, 1975; El Refaei, 1977; KÜrschner et al., 1990) but silica in soil inhibits blast incidence (Paik, 1975; Datnoff et al., 1991; Teng et al., 1991) even at higher nitrogen levels (KÜrschner et al., 1990). The high rate of silica accumulation in lowland fields is the primary reason why blast was first reported a problem in upland rice cultivars. Reports have shown that lowland fields contain ample amounts of silica due to standing water in the paddy (Tschen and Yein, 1984). The physiological mechanism of blast inhibition by silica has been documented (Datnoff et al., 1991; Volk et al., 1958), but its inclusion in blast simulation models has not been done (Teng et al., 1991).

Latency. Latency of infection is affected by the age and degree of susceptibility of the cultivar, temperature, dew duration, and soil moisture. Linear (Yoshino, 1971, 1972); non-linear (Sekiguchi and Furuta, 1970) functions have been generated to show the negative effects of mean temperature on latent period. Teng et al. (1991) also reported a decrease in latency of 10 days when temperature increases from 16 C to 27 C. Latency of blast lesions on rice spikelets appears shorter than those present on panicle axes and neck nodes. At a temperature range of 13-33 C, latent periods are 5, 10, and 13 days, respectively for spikelet, panicle axes, and neck node lesions (Teng, 1993).

Lesion expansion. Rate of lesion expansion is influenced by crop age (Kahn and Libby, 1954; Torres, 1986), lesion age (Calvero et al., 1994; El Refaei, 1977; Kato, 1974), and three environmental factors: temperature, relative humidity, and dew period (Chiba et al., 1972; El Refaei, 1977; Kato, 1974; Kato and Kozaka, 1974).

Chiba et al. (1972) examined lesion growth at different temperatures and found out that exposure of plants to constant temperature of 25 C and 32 C and variable temperature of 32/20 C or 32/25 C in a 12-hour thermal period caused lesions to expand rapidly for the first 8 days and level off shortly thereafter. At 16 C and 20/16 C, the rate of lesion expansion was observed to be slow and constant over the 20-day period (Kato, 1974; Kato, 1976). Lesions expanded more slowly at 20 C and 25/16 C than at higher temperature regimes (Kato, 1974).

Spore production. During epidemic development, temperature, relative humidity, and light influence the sporulation potential of lesions on both leaves and panicles. However, large numbers of spores are produced by 10- to 15-day old leaf blast lesions on plants at seedling stage regardless of environmental conditions (Asaga et al., 1971; El Refaei, 1977; Kato, 1974; Suzuki, 1975; Torres, 1986).

High sporulation potential is possible at 20 C (El Refaei, 1977; Kato, 1974; Kato and Kozaka, 1974; Kato et al., 1970). A subsequent decrease in spore production is seen with increasing temperature; at 15 C and above 29 C, the amount of spores produced by lesions is the same (El Refaei, 1977). Optimum sporulation was found at maximum-minimum temperature combinations of 25/20 C (El Refaei, 1977) and 25/16 C (Kato and Kozaka, 1974). Suzuki (1975) reported also that sporulation does not occur below 9 C or over 35 C and that, the optimum is 25-28 C. Likewise, production is rapid and occurs in shorter periods at 28 C than at 20-25 C (Suzuki, 1975).

High relative humidity favors sporulation (El Refaei, 1977; Kato, 1974; Kato et al., 1970; Suzuki, 1975). The most favorable humidity level is over 93%, but ample spore production is also possible at 85% (El Refaei, 1977). In panicle blast, sporulation of lesions is not as affected by relative humidity and spores are produced at 65% (El Refaei, 1977).

Not much attention has been given to the effect of light on conidial formation. Suzuki (1975) reviewed the effect of light intensity on sporulation. From the review, light indirectly affects sporulation by directly affecting plant resistance. During cloudy days, assimilation of carbon decreases while soluble nitrogen accumulation in tissues increases. When this occurs, physiological activity and resistance of the host are reduced, making plants more vulnerable to pathogen attack. An earlier study by Yoshino and Yamaguchi (1974) supports this argument. They reported that shaded plants have a tendency to undergo 'temporary susceptibility' and become infected. Unpublished laboratory studies at the Division of Entomology and Plant Pathology at the International Rice Research Institute (IRRI), however, revealed that sporulation among *P. grisea* isolates grown *in vitro* is enhanced by exposing cultures to continuous fluorescent light for 5-7 days. This practice of enhancing spore production should be explored further to unravel the real effects of solar radiation and sunshine duration on blast incidence.

CURRENT STATUS OF BLAST DISEASE MANAGEMENT

There has been much research done on the different aspects of effective blast management, including new approaches in biotechnology and quantitative epidemiology. Rice chromosomal mapping that locates specific loci responsible for partial blast resistance is used to identify cultivars as sources of resistance (Bonman et al., 1992). Computer modeling and the use of Geographic Information Systems (GIS) to understand spatial and temporal dynamics of blast pathosystem are epidemiological approaches in blast management (personal communication, Paul S. Teng, IRRI).

Over the years, Integrated Pest Management (IPM) and sustainable agriculture have provided an increased use of resistant cultivars in most tropical rice systems. In temperate irrigated ecosystems like Japan, Korea, China, and Taiwan, however, blast management remains heavily dependent on fungicide use (Ou, 1980; Teng, 1993). Bonman and co-workers (1992) advocated the deployment of partial resistance among rice cultivars in the developing countries. They noted that knowledge-based technologies are not easily adopted by farmers and disseminated at the farm level. Use of cultivar mixtures with different partial resistance to blast has also been tested as a component of disease management (Bonman et al., 1986). Biological control, although potentially useful in blast management, has not been successfully applied in production areas because of inconsistencies on the results obtained from laboratory and field trials (Gnanamanickam and Mew, 1990). Knowledge on the population dynamics of the biological control agents is limited and needs to be thoroughly studied (personal communication, Paul S. Teng, IRRI). A blast management toolkit that integrates all blast management techniques, including policy and communication instruments is proposed by Teng (1993). The toolkit puts rice ecosystems in three scenarios based on current cultural and disease management practices while also considering other components of farming systems like attitudes of rice farmers toward disease management schemes. The toolkit will be particularly important in the developing countries that do not have the resources or lack the expertise to manage blast by complicated strategies. The work at IRRI is underway to formulate the components of the blast management toolkit (personal communication, Paul S. Teng, IRRI).

RICE BLAST FORECASTING

Simulation studies using data from tropical and subtropical areas have shown that temperature changes may bring about years that are blast conducive (Teng, 1993; Teng and Yuen, 1990). Forecasting techniques could be used to identify which years are conducive and whether fungicide application would be cost-effective or risky under those conditions. Rice farmers in most developing countries demand immediate results once disease problems are encountered. For this reason, fungicides are still the preferred control measure against diseases like blast (Ou, 1980), and to counter this, better forecasting schemes for tropical conditions are solely needed.

In Japan, a computer model was developed by Uehara and co-workers (1988) to forecast the occurrence of *P. grisea* in relation to prevailing weather (meteorological) conditions. The model named BLASTAM, estimated leaf blast occurrence and development at the Hiroshima Prefecture from daily weather data supplied by the Automated Meteorological Data Acquisition System (AMeDAS). Leaf blast predictions were found to be nearly accurate but further improvements to estimate panicle blast development are needed.

Other forecasting systems in Japan employ not only a deterministic approach but also stochastic functions to accurately predict leaf and panicle blast epidemics (Ishiguro, 1991; Ishiguro and Hashimoto, 1988, 1989). In most cases, the leaf blast pathosystem is expressed by deterministic equations generated from empirical data of previous laboratory and field studies. The Monte Carlo method is used in stochastic models to simulate the panicle blast pathosystem. Algorithms to relate fungicide application with decreased disease incidence and functions that estimate yield loss from disease have provided improvements on some forecasting systems in Japan (Ishiguro and Hashimoto, 1991).

In Korea, Kim et al. (1987, 1988) developed a computerized forecasting system based on microclimatic events and then tested it in upland and lowland rice fields. A two-battery-operated microcomputer unit regularly monitored air temperature, leaf wetness, and relative humidity, which were used to predict blast development from estimates of blast units of severity (BUS). BUS were calculated based on algorithms employing logical functions that correlate disease to meteorological variables. The cumulative BUS were then used to predict disease progression. In another situation, Lee et al. (1989) used spore traps to investigate blast outbreaks at Icheon and Suweon, South Korea in relation to temperature, relative humidity, rainfall, sunshine hours, and leaf wetness duration in the field. The amount of spores trapped in samplers was used to predict leaf severity and panicle blast incidence. Differences in disease trends were found between the two sites and were attributed to differences in leaf wetness periods at the sites.

The Institute of Plant Protection at the Zhejiang Academy of Science developed a computerized forecasting system for rice blast in China (Zhejiang Research Group, 1986). Meteorological and biological factors affecting *P. grisea* and disease severity were related to field management, growing area, and cultivars to establish a data base. Models developed using stepwise regression analysis, were used to predict blast disease indices based on 20 meteorological, biological, and cultural factors. Predictive models also exist in Taiwan (Tsai, 1986). Regression equations relating meteorological variables to leaf blast severity on the susceptible cultivar Tainung 67 were the basis for an early disease warning system in Taiwan. The models showed that average relative humidity, hours of relative humidity over 90%, and rainfall were important to predict blast severity (Tsai, 1986).

Rice blast outbreaks in the Middle East also resulted in the development of forecasting tools. In Iran, Izadyar and Baradaran (1990) made a 6-year study of blast infection on five local cultivars sown four times a year. At every sowing date, minimum temperature and the number of days after transplanting (NDAT) until the appearance of leaf blast lesions were recorded. Regression models were then generated to establish relationships between NDAT and maximum leaf blast severity, and between NDAT and minimum temperature. Model predictions showed increases in leaf blast severity due to decreases in NDAT and increases in minimum temperature. In Egypt, a forecasting system was developed following a 1984 epidemic. The system includes close monitoring of weather and disease incidence in relation to cultural management practices and current blast management strategies (Kamel and El Sharkawy, 1989). A cost-benefit analysis was incorporated to determine if controlling the disease would bring benefits to farmers.

The model named EPIBLA (EPIdemiology of BLAst) simulated incidence of blast and made 7-day forecasts of disease progression in tropical rice areas in India (Manibhushanrao and Krishnan, 1991). EPIBLA was developed following the multiple regression equation

$$Y = \alpha + ß_1X_1 + ß_2X_2 + \ldots + ß_nX_n$$

where Y is either the number of spores/m^3 of air or disease incidence, α the intercept, ß the partial regression coefficients, and X the predictor variables. In predicting the number of spores in the air, daily values of maximum temperature and maximum relative humidity served as predictors in the equations. The predicted spore amount, and the minimum temperature and amount of dew, summed and averaged, respectively over a 7-day period preceding disease onset were used to estimate disease incidence.

Empirical models were also found useful for forecasting blast in Thailand (Surin et al., 1991). Microscope slides were placed 80 cm above the ground to monitor spore population in different farmers' fields. The correlation between the number of spores over susceptible canopies and severity of disease, together with measurements of environmental conditions were the basis for developing the models. Occurrence of blast was predicted within 7 to 15 days in the field when the number of spores trapped per slide was five or more. Leaf blast incidence was likewise estimated using incidence or severity on the top four leaves or on the third leaf of a rice crop as predictors in regression equations.

In the Philippines, El Refaei (1977), proposed two regression equations to predict the number of lesions in rice seedlings (Y) five days in advance. The first set of equations showed exponential relationship between disease, dew duration in hours (D) and aerial spore concentration (S), i.e.,

$$Y = 0.195e^{0.413D} \text{ at } S < 250 \text{ spores/m}^3$$

$$Y = 0.989e^{0.318D} \text{ at } S \geq 250 \text{ spores/m}^3$$

where e is the exponential function equivalent to 2.718. The second equation as shown below, depicted a polynomial relationship, i.e.,

$$Y = 2.9 - 0.945D - 0.010S + 0.152D^2 + 0.004DS - 8.000\times10^{-9}D^2S^2$$

where DS is the factor of dew duration (D) and aerial spore concentration (S).

FORECASTING STRATEGIES: LESSONS FROM SELECTED PATHOSYSTEMS

Innovative approaches to rice blast forecasting that consider several meteorological factors occurring during or before the growing season can be explored to predict disease outbreaks with accuracy. Methodologies developed from other pathosystems offer new insights for predictive models for blast in tropical and subtropical rice areas. One area of interest is the use of the WINDOW program (Coakley, 1988; Coakley et al., 1982, 1985, 1988a, 1988b) which explores ways by which several meteorological factors from weather data are characterized and related to different disease parameters. The program, recently renamed WINDOW PANE (Calvero and Coakley, 1993, unpublished), was first applied in wheat-Puccinia stripe rust pathosystem in the Pacific Northwest in the United States (Coakley et al., 1982, 1988a). Using over 10-12 years of weather and disease data, various meteorological averages were generated and their correlation to disease examined using a time sequence search done at different segments of the growing season. Models were developed through regression analysis with factors highly correlated to disease as predictor variables. As this technique provides an excellent way of characterizing the environment as a few meaningful factors (Campbell and Madden, 1990), WINDOW PANE was also used in wheat-Septoria blotch pathosystem to generate models to be used in forecasting that disease (Coakley et al., 1985).

Several statistical techniques can be used to look into weather influences on blast. Although useful, path coefficient analysis (or structural equation analysis) has not been extensively applied to this type of research. The goal of the analysis is to provide explanations of observed correlations by constructing models of cause-and-effect relations among variables (Johnson and Wichern, 1992). In using the technique to forecast blast, path analysis can identify the kind of influence (direct or indirect) weather factors may exert on disease, in a way revoking or supporting previously reported relationships. As an example, precipitation frequency and degree-day periods were previously reported to be important weather factors in pepper-Phytophthora blight pathosystem. With the use of path analysis, however, these factors were found not to exert any influence at all on disease progression (Bowers and Mitchell, 1988; Bowers et al., 1990). They found total rainfall (which was also observed to be indirectly influencing other unrelated weather factors such as temperature) to be the most important weather factor influencing blight epidemics.

Multivariate statistical procedures are seldom used in disease forecasting primarily because of their computational difficulty. The exploratory nature of these analyses, however, still warrants usage in blast forecasting research. The work on lettuce-downy mildew pathosystem is probably the most recent study that used multivariate analysis in forecasting the disease (personal communication, Harald Scherm, University of California at Davis; Scherm and Van Bruggen, 1991). The framework of this study used discriminant analysis procedures to determine infection periods of the pathogen, *Bremia lactucae*, based on three weather variables: temperature, relative humidity, and leaf wetness. The goal is to identify which of these weather variables are most important in separating days with infection occurring from days with no infection occurring. The researchers used stepwise discriminant to initially identify these variables and then the canonical discriminant procedure to pick out the final weather variables that had direct influence on infection period.

The purpose of this research is to use the techniques discussed above to identify environments favorable to rice blast as a precursor to developing forecasting models at one temperate and four tropical locations in Asia. The WINDOW PANE program was first used to search for weather factors correlated to leaf and panicle blast severity or incidence. Linear regression procedures were then used to develop predictive models for each site using these weather factors as predictors. The next step was to use path coefficient analysis to determine the weather factors exerting large direct effects on disease. The last phase was to explore multivariate procedures inorder to investigate the effect of sowing dates on proneness of tropical rice to blast. The procedures included cluster analysis to generate blast proneness groups among sowing dates, principal component analysis to characterize these groups, and discriminant analysis to allocate a new sowing date to any of the proneness groups. The multivariate methods, although exploratory in nature, are new approaches for predicting blast outbreaks in the tropics. Limitations of the predictive models developed at each site and statistical methods used are also discussed.

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CHAPTER II
DEVELOPMENT OF PREDICTIVE MODELS FOR RICE BLAST BASED ON FAVORABLE ENVIRONMENTS

ABSTRACT

Models predicting rice blast on susceptible cultivars at Icheon in South Korea, Cavinti and the IRRI blast nursery in the Philippines, and Sitiung and Gunung Medan in Indonesia, were generated using meteorological factors found by the WINDOW PANE program to be highly correlated with disease. Stepwise and r-square regression procedures were used to develop models using normal and transformed values of both response and predictor variables. Dominant factors in models differed between sites, disease parameters, and cultivars. At Icheon, relative humidity and rainfall factors were dominant. Temperature, rainfall, wind speed and relative humidity factors were components of the models at the sites in the Philippines. Factors of rainfall, temperature, and solar radiation were important at the Indonesian sites. The predictive ability of models was verified using Allen's Predicted Error Sum of Squares (PRESS) statistic and by estimating disease for observations not included in model building. Effects of time of sowing, nitrogen amount, and temperature increase on predicted values of blast were also determined using an analysis of variance test. Simulation for extrapolating values for missing observations in weather databases is discussed.

INTRODUCTION

Blast disease, caused by the fungus *Pyricularia grisea* (Cooke) Sacc. (Rossman et al., 1990) (teleomorph= *Magnaporthe grisea* Herb. (Webster, 1980)), remains a potential threat to rice production in both temperate and tropical rice regions in spite of extensive efforts to study different aspects of the pathosystem (Teng, 1993). The ability of the pathogen to infect different stages of rice growth, the constant change in race or lineage structure among pathogen populations, and its adaptation to both upland and lowland rice ecosystems, are indications of its resilience to changing environments (Bonman et al., 1992; Teng, 1993).

Intensity or severity of an epidemic as dictated by climatic variability is a grave concern in disease management. Not only do climate variations directly affect disease development, they may also predispose the host to a more severe pathogen attack (Coakley, 1988) or inhibit success in applying control measures (Decker et al., 1986). Studies pertaining to environmental effects on incidence and severity focus primarily on temperature, relative humidity, rainfall, and leaf wetness effects (Barksdale and Asai, 1961; Bhatt and Chauhan, 1985; Chiba et al., 1972; El Refaei, 1977; Hashioka, 1965; Kato, 1974, 1976; Kato and Kozaka, 1974; Kim and Yoshino, 1987; Suzuki, 1975; Yoshino, 1972). However, effects of light, soil moisture, and soil nutrients on blast development have also been investigated (Beier et al., 1959; Datnoff et al., 1991; El Refaei, 1977; Gill and Bonman, 1988; KÜrschner et al., 1990; Suzuki, 1975; Yoshino and Yamaguchi, 1974).

Several methods for forecasting blast have been examined, tested in field conditions, and evaluated for accuracy. Researchers in Japan and Korea were the first to develop concise and extensive disease warning systems for blast in the temperate rice regions of Asia since large scale epidemics cause tremendous reductions in yield and revenues on a consistent basis (Kim and Kim, 1991; Kim and Yoshino, 1987; Kim et al., 1987, 1988; Ishiguro, 1991; Ishiguro and Hashimoto, 1989; Lee et al., 1989; Sasaki and Kato, 1971). In tropical and subtropical areas such as India, Taiwan, Philippines, Thailand, Iran, and China, forecasting schemes have also been formulated (Manibhushanrao et al., 1989; Surin et al., 1991; Teng et al., 1991; Tilak, 1990; Tsai, 1986; Zhejiang Research Group, 1986) but not fully applied to predict disease occurrences in the field. The farmers' attitudes toward forecasting schemes and the frequent failure of information transfer from research to extension workers to farmers inhibit the use of forecasting systems in developing countries (Kable, 1991).

Recent advances in disease forecasting of other pathosystems offer new insights into forecasting strategies for rice blast. An example to this is the use of the so called WINDOW program (renamed WINDOW PANE to avoid confusion with Microsoft Windows) developed to assist in the identification of meteorological factors that can be used to predict disease severity or incidence (Coakley, 1988; Coakley et al., 1982, 1985, 1988a, 1988b). First applied to *Puccinia striiformis*, applicability of WINDOW has been extended to *Septoria tritici* in United States. The computer program, as reviewed by Campbell and Madden (1990), provides an excellent way of categorizing weather variables into several meteorological factors measured at different times in the cropping season. The key procedure in WINDOW is the definition of variable-length time periods called windows beginning on, before, or after the crop growing season. A window consists of 9 smaller subsets, the first being the full-length subset and the other eight being progressively smaller. For every window subset, various meteorological factors are calculated and examined for correlation to disease severity. Once factors with high correlation to disease are found, linear regression techniques are then used to develop predictive models.

Application of the techniques described above to blast have been limited by the relatively few observations available from blast studies or surveys from areas in the developing countries. Coakley (1988) and Coakley et al. (1988a) suggested a minimum requirement of 8-12 years for single-season crops. In the case of a multi-season crop like rice, 8-12 planting times or at the minimum, four years of disease observation, with rice planted three times a year are required. Nevertheless, applicability of WINDOW PANE to blast warrants further investigation as an initial step in building sound forecasting systems intended for use at key hot-spot areas in Asia. This study was undertaken for three reasons: 1) to generate predictive site-specific models of rice blast at five locations in Asia using WINDOW PANE and regression techniques; 2) to establish relationships between the environment and blast severity or incidence; and 3) to test the robustness of models for predictions using validation and experimentation procedures.

MATERIALS AND METHODS

Sites. Five locations in Asia served as case study sites: Icheon in South Korea (lat 37°2′ N, long 127°5′ E), Cavinti (lat 14°17′ N, long 121°30′ E) and the International Rice Research Institute (IRRI) blast nursery (lat 14°11′ N, long 121°15′ E) in the Philippines, and Sitiung (lat 1°14′ S) and Gunung Medan (lat 1°16′ S, long 101°36′ E) in Indonesia. All sites are situated in the tropics, except for Icheon which is a temperate site. The majority of rice growing areas in South Korea are devoted to lowland cultivation (Herdt and Capule, 1983), whereas, sites selected in the Philippines and Indonesia are used for upland cultivation.

Disease databases. At Icheon, 16-years of disease data (Fig. II.1a) were obtained from Dr. C.K. Kim of Rural Development Administration (RDA) at Suweon, South Korea. The data have lesion number per plant and percent panicle blast incidence measured from plots planted to a blast susceptible cultivar, Jin heung (days to maturity ≈ 100-110) and treated with two nitrogen rates at 110 and 220 kgN/ha. Disease observations were made during 1974-1989 at several assessment dates starting at the transplanting date, 26 May (day of year = 146). Nine disease parameters were generated for the site: lesion numbers measured at 49 (maximum lesion) and 68 (final lesion) days after transplanting (DAT), and panicle blast incidence taken 84 DAT, done separately for two nitrogen treatments, and the same three parameters above but with combined nitrogen data sets. A total of 16 and 32 observations per disease parameter under separate and combined data sets, respectively, were used for WINDOW PANE and regression analyses at Icheon.

At Cavinti, data were obtained from blast validation and site-comparison experiments conducted during 1992-1993. Both experiments had blast-susceptible rice cultivars IR50 (days to maturity ≈ 105-110) and C22 (days to maturity ≈ 120-130) sown under upland conditions in 4 m^2 miniplots using a 20 cm x 20 cm row spacing. These cultivars thrive in different rice ecosystems; IR50 predominate in lowland ecosystems, while C22 does best in upland ecosystems. In the blast validation experiment, disease data (Fig II.1b) were obtained from five sowing dates: 22 June 1992, 24 December 1992, 15 March 1993, 22 June 1993, and 20 July 1993. In each sowing date, three replications and three nitrogen treatments at 60 kgN/ha, 120 kgN/ha, and 240 kgN/ha were used. The site-comparison study had two sowing dates done in July and August in 1993 using 80 kgN/ha nitrogen treatment and with three replications (personal communication, Aurorita Calvero, IRRI). In the validation experiment, data of percent diseased leaf area (DLA) per plot and panicle blast severity were measured, respectively, from onset to maturity at weekly intervals, and at maturity using an assessment key (Kingsolver et al., 1984). On the other hand, leaf blast and panicle blast severities were provided by A. Calvero of IRRI for the site-comparison experiment. In generating predictive models at Cavinti, three disease parameters per cultivar were used, i.e. DLA measured 83 days after sowing (DAS) on C22 and 91 DAS on IR50 (maximum DLA), DLA taken at maturity (final DLA), and panicle blast severity. Disease observations from the nitrogen treatments averaged across replications in both experiments were combined to generate 17 observations per blast parameter per cultivar available for WINDOW PANE and regression analyses.

At the IRRI blast nursery, blast data were obtained from 1989-1992 sowings of IR50 planted in seedbeds using a 25 cm x 25 cm hill spacing and with 120 kgN/ha nitrogen treatment. Three replications were used at every sowing date, each date separated three weeks from the previous one. Percent DLA per plot were taken at bi-weekly interval from disease onset to maturity; panicle blast severity was measured at maturity (approximately 105 DAS) (Fig. II.1c). DLA measured at maturity (final DLA) and panicle blast severity were the disease parameters used in the analysis as observation dates for maximum and final DLA coincided. A total of 32 observations per disease parameter were available for WINDOW PANE and regression analyses at the nursery. It should be noted here that plots at this location were planted with blast-infected spreader rows, whereas other sites had on naturally occurring disease. Therefore, disease spread at the nursery was basically artificial as blast inoculum coming from the spreader rows was continuously available all throughout the year (personal communication, Jose Bandong, IRRI).

Blast data on C22 cultivar taken during 1980-1981 at Gunung Medan and during 1981-1982 at Sitiung were provided by Mr. S. Darwis of Sukarami Research Institute for Food Crops (SARIF) in Indonesia. Final readings of diseased leaf area (measured at 68 DAS) and panicle blast severity (measured at 100 DAS) were expressed as disease indices and obtained from plots sown with the cultivar at various sowing dates (Fig. II.1d). These readings served as disease parameters for WINDOW analysis and for generating the models at the two sites. A total of 10 and 12 observations were available at each site for leaf and panicle blast parameters, respectively.

Extrapolation procedures for weather databases with missing values. The available database at Icheon during 1974-1989 contained only the May to August daily values of weather variables. In the database, 80%, 56%, 63%, and 67% of rainfall observations were missing during 1986-1989 respectively; no wind speed values were available during these years. At Gunung Medan and Sitiung, only the monthly mean values of maximum and minimum temperatures, relative humidity, solar radiation, and total rainfall from September to June during 1980-1981 and 1981-1982, respectively, were available.

Simulation and regression techniques were employed to extrapolate values for missing rainfall and wind speed observations at Icheon during 1986-1989. At the Indonesia sites, simulation and time series forecasting were used to generate daily values of weather variables from available monthly means. SIMMETEO, a microcomputer-based weather generator was used to simulate daily values of rainfall in millimeters per day (mm/day), maximum and minimum temperatures in degrees Centigrade (C), solar radiation in megajoules per square meter (MJ/m^2), sunshine duration in hours (h), relative humidity in percent (%), and wind speed in meters per second (m/s) (Geng et al., 1988). Monthly means of fraction of wet days calculated as the ratio of number of wet day periods to total number of days in a month, total rainfall relative to wet day periods, maximum and minimum temperatures, solar radiation or sunshine duration, relative humidity transformed into vapor pressure expressed in kilopascal (kPa), and wind speed (Tables II.1a-b) were needed by SIMMETEO to generate daily values. Although its application has been limited, performance of SIMMETEO had been tested at Los Baños in the Philippines (tropical) and at Wageningen in the Netherlands (temperate) with simulated weather values showing reasonable agreement with actual values (Geng et al., 1985a, 1985b). It is for this reason that aside from its requirement for simple input data and the results from Geng et al. (1985a, 1985b), the weather generator was used as a method for extrapolating missing weather values.

As the Icheon database did not have full year data (full year data have 1-365 or 1-366 days), completing a 12-month input data set needed by SIMMETEO was necessary. Prior to regression analysis, similarity in weather conditions between Icheon and Suweon (lat 37°16′ N, long 126°6′ E) were tested using canonical discriminant analysis in order to have a statistical basis for using the latter site's data in the succeeding analysis. Only the May-August 1977-1985 daily values of weather variables were used to differentiate Icheon from Suweon because no data were available during 1974-1976 at the latter site and missing values existed in the Suweon database during 1986-1989. The stepwise regression procedure was then used to develop regression equations that estimate monthly values of the fraction of wet days, total rainfall, and wind speed at Icheon. Monthly means of other available weather variables from Icheon 1974-1989 and Suweon May-August 1977-1989 databases were used as predictors in the equations.

Regression models were chosen that gave a substantial decrease in mean square error (MSE) and narrow prediction errors after cross-validation tests using observations excluded in model development. These models were then adjusted for lag 1 serial correlation to minimize autocorrelation among adjacent observations. Regression estimates of monthly total rainfall, fraction of wet day period, and wind speed for each year during 1986-1989 completed the May-August values in the input data set of SIMMETEO. The January-April and the September-December values in the input data set were obtained from the Suweon data. Daily values simulated from the months extracted from Suweon, however, were excluded from the final Icheon weather database.

For the two Indonesia sites, the 12-month input data sets required by SIMMETEO were completed using a different method. Monthly mean values in July and August (months with no monthly means available) were estimated using the Winter seasonal smoothing time series forecasting method available in the STATGRAPHICS software (STSC, 1991). This was done because no sites adjacent to Gunung Medan and Sitiung have weather data from which information could be extracted for regression analysis. The final weather databases of the two sites, however, excluded simulated daily values of variables in July and August. The nonavailability of actual trend of values in July and August which could have been used to compare simulated data with actual values, was the basis for excluding these months from the databases of the two Indonesia sites.

A 100-year simulation was done for each year in question at the three sites. The canonical discriminant analysis procedure (PROC CANDISC) of Statistical Analysis System (SAS) software (SAS Institute, Inc., 1988) was employed to determine which simulated years best represent actual years using monthly mean values of weather variables as attributes and considering observed and simulated values as two distinct groups. Simulated daily values from years with a likelihood ratio and a probability greater than F (P > F) values nearest to 1 were used to fill in the missing rainfall and wind speed observations at Icheon, and/or complete the entire weather databases for Gunung Medan and Sitiung.

Meteorological databases. Daily values of mean, maximum, and minimum temperatures, rainfall, relative humidity, and solar radiation were available for all sites. Sunshine duration and wind speed were also included in the databases of Icheon and the IRRI blast nursery. The Icheon, Cavinti, IRRI blast nursery, Gunung Medan, and Sitiung weather databases, respectively had 16 (1974-1989), 7 (1987-1993), 8 (1985-1992), 2 (1980-1981), and 2 (1981-1982) years of available data. It should be noted, however, that the Icheon, Cavinti, and Indonesia databases did not have full year data.

All databases from the Philippines sites were obtained from the IRRI Climate Unit; Icheon and Indonesia data were provided, respectively, by Dr. C.K. Kim of RDA and Mr. S. Darwis of SARIF. The list of meteorological factors considered for each site is presented in Table II.2. In particular, factors in consecutive days were counted as described by Shaner and Finney (1976), i.e., only sequences of two or more days that meet a specified criterion were counted and summed for a window subset. For example, 5-, 4-, and 2-day periods with precipitation were counted as 4, 3, and 1 respectively, to come up with a CDWP (consecutive days with precipitation) value of 8 (Coakley et al., 1988a).

The WINDOW PANE program. WINDOW PANE version W1B00003 was used to search for specific meteorological factors correlated with disease parameters (Calvero and Coakley, 1993, unpublished documentation). This version is a modification of the previous programs written in Fortran 77 developed by Coakley et al. (1982, 1985, 1988a, 1988b). The current version handles 100 observations for analysis, can be used on single-season (diseases occurring once a year) and multi-season diseases (diseases occurring several times a year), and has an improved user-friendly interface and data management. The program runs on a microcomputer equipped with at least 2 megabytes (MB) random access memory (RAM) and with or without a math co-processor.

The general procedure in WINDOW PANE is the identification of variable-length time periods (windows) (Fig. II.2) beginning on, or before, or after the crop growing season (Coakley et al., 1982, 1985, 1988a, 1988b). Each window consists of 9 smaller time periods (window subsets), the first being the full length window, and the remaining 8 being progressively smaller subsets. At a certain starting date, a window moves forward across the weather database following a specified time increment. After each window movement, weather factors are estimated for every window subset either by summing, averaging, or obtaining frequencies of variables in weather databases. Correlation of these factors to disease is then calculated for each window subset. Initially, a longer window subset duration (e.g. 7 or 10 days) is used to search for weather factors correlated with the disease. Once such factors are determined, a shorter duration of 1 day is specified to identify the precise time period for factors with highly significant correlation coefficients.

WINDOW PANE analysis. In using WINDOW PANE, the initial window started 24 days before transplanting (DBT) at Icheon; 30 days before sowing (DBS) at Cavinti, at the IRRI blast nursery, and at Sitiung; and 29 DBS at Gunung Medan (Fig. II.2). Differences in windows are due to the limitations of available data from the weather database; for e.g. Icheon, Cavinti, and the Indonesia sites did not have data for full year cycles. The initial time increment for windows to move across the weather database was set 10 days for all sites, except at Icheon where windows were moved four days. Window subset duration for all sites were initially set 10 days apart, i.e., the smallest and full-length subsets were 10 and 90 days long, respectively (Fig. II.2). At Cavinti, however, subset durations were initially set 8 days apart with smallest and full-length subsets at 6 and 70 days, respectively (Fig. II.2). For each window set, factor values were calculated, then correlation with disease parameters obtained. Meteorological factors giving high and significant correlation coefficients at $P \leq 0.05$ were further analyzed using subset durations of one day to identify the precise duration that gave the highest correlation with disease.

Model development and evaluation. From those meteorological factors identified by WINDOW PANE, the choice of predictor variables to develop models was narrowed down to those that had predictive ability and that would aid in any kind of disease control decisions. Rules were set for choosing weather factors that were correlated with leaf and panicle blast parameters. For leaf blast, factors chosen started on, or before, or after planting (either direct-seeded or transplanted), covered the estimated disease onset and had ending dates occurring on or before 45 days after planting. For panicle blast, factors had starting dates following the rule for leaf blast but durations ending on or before the flowering stage (approximately 30 days before maturity according to Yoshida, 1981) of the cultivar were chosen.

Models for blast parameters were developed at each site using the regression procedure (PROC REG) in SAS. Stepwise and r-square methods were used to identify the factors that predict blast severity or incidence and meteorological factors and nitrogen amount were used as predictor variables. Analysis was carried out with normal and transformed values of both the response and predictor variables. Natural logarithmic and power transformations up to the $a^{1/6}$ (where a is either the response or predictor variable) were applied to normalize the distribution of values and to linearize the relationships between variables. The number of predictors included in the models was set to a maximum of four weather factors. Using this setup for the models satisfied the minimum requirement on the ratio of predictors with sample size as suggested by Tabachnick and Fidell (1989) for regression analysis. A one-predictor model, however, was used in Indonesia models because of small sample size (personal communication, Dan Schafer, Oregon State University).

Stepwise regression was applied to determine weather factors (predictors) with both statistical and biological significance. In some instances, however, statistically insignificant factors with $P \geq 0.05$ but which would be biologically important, were also considered in the models. Identification of such predictors from among available variables was facilitated by the r-square procedure based on some statistical criteria: variance inflation factor (VIF) less than two (Coakley et al., 1988a), improvement in adjusted coefficient of determination (R^2) (Myers, 1990; Neter et al., 1989), and low Mallow's CP value (Coakley et al., 1988a; Myers, 1990).

Five models per disease parameter per site were developed and evaluated following some statistical criteria: equal residual variance, normal studentized residual with Shapiro and Wilks P > W near unity (Myers, 1990), low Allen's predicted error sum of squares (PRESS) (Coakley et al., 1988a, 1988b; Myers, 1990; Neter et al., 1989), coefficient of variation (CV) less than 25% (Myers, 1990), VIF values of predictors less than 10 (Myers, 1990), and high adjusted R^2. Likewise, models' percentage accuracy of prediction (ACC %) was estimated from contingency quadrants (Fig. II.3). Using specified cutoff points (Table II.3), ACC was estimated as described by Coakley et al. (1988a, 1988b), i.e.

$$\frac{a}{b} \times 100 \qquad \text{(Eqn. II.1)}$$

where a is the total number of observations in quadrants I and IV, and b is the total number of years for which predictions were made.

Model validation. The predictive ability of models was verified using the PRESS statistic and estimating disease observations excluded in model development. Twenty five percent of the total observations were randomly chosen as a validation set in all sites, except at Gunung Medan and Sitiung where this procedure was not followed due to the few observations available. Accuracy of model prediction on a validation set was determined by three methods: 1) computing the average prediction error (MDIFF) (prediction error is the difference between predicted and actual disease value); 2) estimating the length of prediction error (LPE) calculated as the difference of minimum prediction error from maximum prediction error; and 3) determining where estimates fell in the contingency quadrant. Models with low PRESS values, MDIFF near zero, narrow LPE, and no over or underprediction made for observations in the validation set, were judged as best and considered as the predictive models for blast.

Model experimentation. Robustness of the best models was tested through analysis of variance test by estimating leaf and panicle blast severities under 0, 1, 2, 3, and 4 C increases in temperature for three sowing dates at the tropical sites, and a single date at Icheon. First, monthly mean values of maximum and minimum temperatures were extracted from existing weather databases to be used as input data to SIMMETEO. For every adjustment made on the temperature variables in the input data set, a 20-year weather database was constructed at each site by the weather generator. Disease parameters of blast were then estimated from each constructed database in three hypothetical sowing times set on February 15, June 15, and October 15 in the Philippines and Indonesia sites; and on May 26 at Icheon. Nitrogen amounts at 110 and 220 kgN/ha served as another factor in the analysis for models that include this variable as a predictor.

The generalized linear model procedure (PROC GLM) in SAS was used as an analysis of variance method to test the main effects of three factors on blast: temperature increment, nitrogen amount, and sowing date. Interaction terms were also included in the analysis to examine the combined effects of these factors on disease. Significant interaction terms were further analyzed using linear contrast to see specific factor combination contributing to the significance of interaction. The Tukey-Kramer method ($P = 0.05$) available in PROC GLM was used for making multiple comparisons among treatment means. This method was chosen over the other comparison procedures because the goal was to compare every mean to every other mean. It is also an appropriate method that reduces the possibility of getting false differences between treatment means (Miller, 1985). Power and natural logarithmic transformations were also applied to normalize distribution of points among response variables, to minimize mean square error, and to produce equal spread of residual values.

RESULTS

Extrapolation of values for incomplete weather databases. Regression analysis and simulation were found useful for extrapolating missing values of observations in weather databases. At Icheon, regression analysis was initially used to estimate total rainfall, fraction of wet days, and wind speed to complete input data required by a weather generator, SIMMETEO (Geng et al., 1988) prior to filling-in missing observations.

Total rainfall was found linearly related to vapor pressure and solar radiation (Eqn. II.2) with adjusted coefficient of determination (aR^2) and mean square error (MSE) equal to 0.99 and 0.06, respectively. The function is,

$$RAINT = (1.088\ VP^{1/3} + 14.940\ SOLAR^{-1})^6 \qquad \text{(Eqn. II.2)}$$

where RAINT is total rainfall in mm/month, VP is vapor pressure in kPa, SOLAR is solar radiation in MJ/m^2. From this equation, fraction of wet day (FWD) was then estimated using RAINT in combination with temperature and vapor pressure (Eqn. II.3, $aR^2 = 0.94$, MSE= 0.01) shown as,

$$FWD = -2.770\times10^{-7}\ TMAX^4 - 2.570\times10^{-4}\ TMIN^2 + 0.470\ \ln(VP) + 0.045\ RAINT^{1/3}, \qquad \text{(Eqn. II.3)}$$

where TMAX and TMIN are maximum and minimum temperatures in C, respectively, and ln(VP) is the natural logarithm of vapor pressure. Wind speed (WS) was found linearly related to sunshine duration (SUND), SOLAR, and TMAX (Eqn. II.4).

The model generated for WS gave aR^2 and MSE equal to 0.68 and 0.001, respectively:

$$WS = (1.580 - 0.235\ \ln(SUND) - 6.044\ SOLAR^{-1} - 1.140\times10^{-7}\ TMAX^{4})^{5} \qquad \text{(Eqn. II.4)}$$

Simulated values as chosen by canonical discriminant analysis via likelihood ratio and P> F near unity as criteria, showed almost similar trends with actual monthly weather values at Icheon (Fig. II.4a-b), Sitiung, and Gunung Medan (Fig. II.4c). This suggests that the procedures used could be appropriate for weather data extrapolation especially for databases that have missing values or only monthly means as available information.

Meteorological factors important to disease parameters. Several meteorological factors were found by WINDOW PANE to be correlated with disease parameters at the five sites used. At Icheon, combining disease values of two nitrogen treatments gave low absolute correlation coefficients (r) ranging from 0.36-0.49 (Table II.4a). Analyzing disease parameters separately by nitrogen treatment, however, made large improvements, with absolute r values ranging from 0.53-0.84 (Table II.4a). Highest r was obtained from number of days with relative humidity ≥ 80% (DRH80, r= 0.81) and consecutive days with relative humidity ≥ 80% (CDRH80, r= 0.84) with final lesion number at 110 kgN/ha nitrogen (FL1) as the disease parameter (Table II.4a). DRH80 and CDRH80 also gave high correlation with other blast parameters at Icheon (Table II.4a).

Combining disease readings of nitrogen treatments at Cavinti for IR50 and C22 cultivars did not reduce r values (Table II.4b). Average wind speed (MWS) and average minimum temperature (MMIN), respectively, gave the highest r with maximum and final DLA as blast parameters on IR50 at this site (Table II.4b). Total precipitation (TPREC) and consecutive days with precipitation (CDWP), on the other hand, were also highly correlated with panicle blast severity on IR50 (Table II.4b). In general, MWS, TPREC, and CDWP were negatively correlated with blast on IR50, while MMIN had positive correlation. In C22, TPREC was highly negatively correlated with panicle blast severity but positively correlated with maximum DLA. CDWP, on the other hand, showed positive correlation with final DLA also on C22. Number of days with wind speed ≥ 3.5 m/s (DWS35) had high positive correlation with panicle blast severity and final DLA on C22 at Cavinti (Table II.4b).

Lower correlation coefficients were obtained at IRRI compared to the other sites. The highest r value was at 0.58 for the number of days with maximum temperature > 25 C (DG25C) correlated with final DLA on IR50 cultivar (Table II.4c). Precipitation frequency (PFREQ), consecutive days without precipitation (CDWOP), and CDWP were also important to leaf blast on this cultivar. These factors had positive correlation with final DLA, except CDWOP, which had negative correlation (Table II.4c). Only DG25C, average relative humidity (MRH), DRH80, and CDRH80 had high absolute correlations (r= 0.40-0.52) with panicle blast severity on IR50 at the nursery (Table II.4c).

Contrasting relationships of weather factors with panicle blast on C22 cultivar were found at two sites in Indonesia. At Gunung Medan, most factors were positively correlated with panicle blast (Table II.4d), while it was the opposite at Sitiung (Table II.4e). Rainfall appeared more important with panicle blast at the first location but temperature was significant at Sitiung. Rainfall factors also gave the highest correlation with final leaf blast at Sitiung (Table II.4e). Although there were factors correlated with final leaf blast at Gunung Medan, they were excluded from the analysis because the factors did not have predictive ability. It should be noted that discrepancies between Gunung Medan and Sitiung could be attributed to having few years disease data available at each site (2 years/site) with only one year (i.e. 1981) the same for both sites.

Model development and evaluation. The models generated for each blast parameter at each site are presented in Tables II.5a-g. Most models developed at Icheon for blast using the separate data sets for the two nitrogen (N) treatments included relative humidity and other factors related to rainfall and temperature as predictors (Table

II.5a). Specifically, DRH80 and TPREC were mostly found together in leaf blast models under low N, while CDRH80 with either DOPT (number of days with mean temperature range of 20-27 C), DG25C, or CDWOP were dominant in leaf blast models under high N (Table II.5a). Only one model was generated for panicle blast under low N with TPREC as the sole predictor (Table II.5a). Similarly, DRH80 was the sole predictor of panicle blast under high N (Table II.5a).

In Icheon models, DRH80 had durations that started before transplanting (DBT) and extended more than a month. In the case of leaf blast models, this factor began 5 DBT and extended 34 or 40 days; for panicle blast models, the beginning date was 25 DBT and extended 70 days (Table II.5a). TPREC and CDWOP, on the other hand, had durations that started a day before or 7 days after planting in most cases, and extended either less than or more than a month (Table II.5a). CDRH80 had durations that started three days after planting and extended less than a month. The temperature factors, DG25C and DOPT had durations that started less than 20 DBT and extended 48 and 10 days, respectively (Table II.5a).

At Icheon, high adjusted-R^2 were obtained for models of final lesion number at N level of 220 kgN/ha (FL2) (adjusted-R^2 range= 0.83-0.94) even with the intercept terms (β_0) included (Table II.5a). Improvement of models with low adjusted-R^2, high predicted error sum of squares (PRESS), and over 25% coefficient of variation (CV) values was observed if values of both predictor and response variables were transformed, or, statistically insignificant ($P \geq 0.05$) β_0 terms were removed. An increase in values of the variance inflation factor (VIF) was obtained if β_0 was removed. Accuracy (ACC) of models as based on the contingency quadrant (Fig. II.3) using specified cutoff points (Table II.3) was higher for final lesion number and panicle blast incidence than maximum lesion number regardless of nitrogen level.

For combined data sets of N (Table II.5b) at Icheon, improvement of models was obtained when N was used as another predictor. Panicle blast incidence models gave the highest range of adjusted-R^2 (0.77-0.81) and include factors CDRH80 and DR84 (number of days with rainfall ≥ 84 mm/day) commencing 9 and 25 DBT, respectively. Models of maximum lesion number gave the lowest adjusted-R^2 (0.58-0.59) with DRH80 that started either one or 9 DBT as predictors. These models, however, gave higher ACC values than the panicle blast incidence models (Table II.5b). Models of final lesion number that include DRH80 and CDWP showed moderately high adjusted-R^2 values ranging from 0.73 to 0.77. All final lesion models had significant β_0 terms and thus, those terms were not removed. Transforming the response variables using the $Y^{1/6}$ power transformation produced low PRESS values and normalized the distribution of residual values (Table II.5b).

At Cavinti, models for disease parameters on IR50 include meteorological factors different from those on cultivar C22. Wind speed factor, DWS35 (number of days with wind speed above 3.4 m/s) beginning 10-20 days before sowing (DBS) was the most dominant factor in models predicting maximum and final DLA (Table II.5c). C22 leaf blast parameter models, on the other hand, contain MMIN, rainfall factors PFREQ and CDWP, and MSR (average solar radiation) (Table II.5d). These weather factors had 10-30 days after sowing (DAS) as the beginning date, except for CDWP which was found to be important before sowing. Both the IR50 and C22 cultivars at Cavinti showed slight similarity for factors important to panicle blast with rainfall factors being dominant predictors (Table II.5c-d). Frequency of rainfall was more important to IR50 than total amount of rainfall; whereas, total amount of rainfall estimates panicle blast severity on C22 better.

Incorporating nitrogen as another predictor in the models of either cultivars at Cavinti produced insignificant regression coefficients ($P > 0.05$) (Tables II.5c-d). Nevertheless, its inclusion in the models was warranted in order to consider its effect on the blast pathosystem. Higher adjusted-R^2 and CV values were observed among models for C22 than for IR50 at Cavinti, although ACC values of models were roughly similar for both cultivars (Tables II.5c-d). All Cavinti models were found to contain predictors with VIF values mostly less than 10, except in some instances for IR50 panicle blast severity models where VIF exceeded this cutoff (Table II.5c).

Temperature, relative humidity, and rainfall factors were found important in predicting disease at the IRRI blast nursery, although, a factor related to wind speed (MWS) was also included in the models (Table II.5e). Temperature factor DG25C occurring either 30 DBS or 20 DAS was important in estimating final DLA together with CDWOP occurring either 10 DBS or 30 DBS (Table II.5e). Although, 80% of the final DLA models included two DG25C factors starting at different times, VIF values of regression coefficients remained less than two, which suggested non-multicollinearity among these variables. Panicle blast models included DG25C and MRH as predictors, both beginning 20 DBS (Table II.5e), with a longer duration of 94 days required by the latter. Low adjusted-R^2 and ACC values were reported for all IRRI models. Panicle blast severity models gave the lowest adjusted-R^2 range at 0.28-0.29 and an accuracy of 62% (Table II.5e).

Models for the two Indonesia sites were limited to one predictor variable because of few observations involved in the analysis. Likewise, no model was developed that estimates leaf blast at Gunung Medan as no factor satisfied the rules set in choosing variables with predictive ability (see Materials and Methods). Rainfall factors, PFREQ and CDWP that started one to 11 DAS were found important in estimating panicle blast index at Gunung Medan (Table

II.5f). Temperature factors DG25C, DOPT (number of days with mean temperature of 20-27 C), and CDOPT (consecutive days with mean temperature of 20-27 C) beginning either at 10 DBS or at sowing time were the dominant predictor variables for panicle blast at Sitiung (Table II.5g). High adjusted-R^2, and low CV and PRESS values were obtained from the models at Gunung Medan (Table II.5f), although accuracy (ACC) appeared relatively higher at Sitiung (Table II.5g). Average solar radiation (MSR) occurring zero to 30 DBS dominated the predictors in the final leaf blast index models at Sitiung with TPREC found in one model (Table II.5g). Adjusted-R^2 values were low (range= 0.35-0.43) in Sitiung's leaf blast models. Two out of five models, however, had improvements in adjusted-R^2 when insignificant β_0 terms were removed. Removal of the intercept term, however, did not significantly increase the ACC values or reduce PRESS (Table II.5g). Transformation of both predictor and response variables, likewise, did not improve predictions.

Model validation. Validation of models was done by making predictions for randomly selected observations not included in model development and by comparing the PRESS values among the models generated. In Gunung Medan and Sitiung models, however, validation was done using just PRESS because of few observations involved in the analysis.

Models for separate data sets of two N levels at Icheon were validated using 1978 and 1983 disease assessments.

Using model accuracy (ACC) from the contingency quadrant (Fig. II.3 and Table II.3) as a criterion, no over or underprediction of actual observations was observed from models of panicle blast incidence (Table II.6a). Most underpredictions were shown, however, when estimating 1983 disease value from models of maximum and final lesion numbers, although, all final lesion models at 110 kgN/ha also overpredicted disease in 1978. Final lesion models and the sole model of panicle blast incidence at 110 kgN/ha gave average prediction error (MDIFF) values nearer to zero than the other disease parameter models (Table II.6a). Length of prediction error (LPE) on the other hand, were wide in all the Icheon models, except, for panicle blast incidence models at 220 kgN/ha which had LPE values ranging from 22-32 % incidence (Table II.6a).

Panicle blast incidence models developed from the combined data sets at Icheon did not over or underpredict actual disease observations using data from 1976, 1978, 1979, and 1988 as validation set (Table II.6b). These models had MDIFF near zero and a narrow LPE range at 21.5-25.3 % incidence. Final lesion models gave the least MDIFF values (-4.0-2.4) but not much narrower LPE than panicle blast incidence models. Three of the five final lesion and maximum lesion models either over or underpredicted half of the validation set (Table II.6b).

At Cavinti, actual panicle blast severity taken at DY 292 in 1993 was underpredicted by all models for IR50 and two of the models for C22 (Table II.6c). No inaccuracy was observed with the models of maximum and final DLA in either cultivars. Near zero MDIFF and narrower LPE values were also observed with these models than those with panicle blast severity models. On the other hand, models of disease parameters at the IRRI blast nursery gave some degree of inaccuracy in estimating five observations in the validation set (Table II.6d). All final DLA models either over or underpredicted 60% of the actual observations, except model IV which gave 40% underprediction. All panicle blast severity models at the nursery overpredicted 40% of observations in the validation set. These models, however, produced MDIFF values nearer to zero and narrower LPE than final DLA models at the site (Table II.6d).

Model experimentation. The best models from each site were chosen using the statistical criteria described earlier (see Materials and Methods) and model robustness was tested for predicting the disease parameters under hypothetical temperature increases, and under changing N level and sowing date. Using models from the combined data sets of two N levels at Icheon, a highly significant temperature (T) effect was found on predicted values of maximum ($P = 0.0001$) and final lesions ($P = 0.0001$), and panicle blast incidence ($P = 0.006$). Significantly different disease levels were shown also with increasing nitrogen (N) amounts at the site. Although all factors produced highly significant main effects, no significant T x N interaction was found (maximum lesion: P= 0.97; final lesion: P= 0.64; panicle blast incidence: P= 0.99).

Increasing temperatures resulted in considerable increases in panicle blast incidence and decreases in leaf blast lesion numbers at Icheon (Table II.7a). In addition, an increase from 0 C to 1 C and from 3 C to 4 C in temperatures did not produce significant changes in final lesion number and panicle blast incidence, respectively (Table II.7a). In general, leaf blast lesion numbers and panicle blast incidence were higher at 220 kgN/ha than at 110 kgN/ha at the site (Table II.7a).

Highly significant T, N, and sowing date effects (S) (P= 0.0001) were observed with maximum DLA on IR50 at Cavinti. Maximum DLA on C22, however, was not affected with changing N amounts (P= 0.49) (Table II.7b). Obviously, insignificant T effect was obtained with final DLA on IR50 and panicle blast severity on C22 because the models used to estimate these parameters do not include temperature terms. Following significant temperature effects on maximum DLA at Cavinti, IR50 showed increasing disease at low temperature. In contrast, high temperature seemed favorable for both maximum and final DLA on C22 cultivar (Table II.7b).

Nitrogen had no effect on final DLA on either IR50 (P= 0.49) or C22 (P= 0.59) cultivars at Cavinti. An increase in N, however, favored maximum DLA but not panicle blast on IR50 (Table II.7b). Planting IR50 and C22 at Cavinti at different times regardless of temperature increment and N amount also had a significant effect on leaf blast. Planting IR50 during February (dry) gave the least maximum and final DLA. Highest DLA values were obtained from the June (wet) planting (Table II.7b). Planting C22 during June, on the other hand, may also produce high leaf blast, but the lowest predicted disease was given with sowings made in October (very wet). Trends in panicle blast were similar in both cultivars at Cavinti, with high and low severities during February and October, respectively, regardless of temperature and nitrogen amount applied (Table II.7b). Only the T x S interaction for final DLA on C22 was significant ($P = 0.0001$). Further analysis of this interaction with linear contrast showed disease varied among observations ($P < 0.05$) in all T and S combinations, except at zero temperature increment in February ($P = 0.11$), the sowing made in June with zero ($P = 0.35$) and one ($P = 0.40$) temperature increments, and in October with two ($P = 0.20$), three ($P = 0.98$), and four ($P = 0.47$) degree increase in temperature.

Significant temperature and sowing date effects on blast ($P < 0.05$) were found at the IRRI blast nursery. Likewise, significant T x S interactions were obtained for final DLA ($P = 0.05$) and panicle blast severity ($P = 0.02$). All temperature increments, except zero increase gave the same final DLA level (Table II.7c), with high temperature favoring disease. With panicle blast, however, low temperatures were found to increase severity (Table II.7c).

Planting IR50 at the nursery in June (wet) gave high predicted final DLA and panicle blast severity values; lowest severity occurred in February (dry) (Table II.7c). Linearly contrasted predicted disease values under various T and S combinations have shown no differences in panicle blast severity at zero ($P= 0.10$) and one ($P= 0.52$) degree temperature increments during the October (wet) planting. Only 33% of all T and S combinations, however, gave significant contrasts ($P< 0.05$) with final DLA.

No temperature terms were included in panicle and leaf blast index models at Gunung Medan and Sitiung because the temperature effect was obviously insignificant in these parameters (Table II.7d). On the other hand, the panicle blast severity model at Sitiung has a temperature term which produced significantly different ($P= 0.0001$) predicted values with decreasing severity at increasing temperatures (Table II.7d). The June (slightly dry) planting at Sitiung gave a high leaf blast index; planting during October (wet) gave the lowest. Trends in panicle blast likewise differ at both sites at various sowing times. Highest and least panicle blast indices were observed during the February (dry) and June (wet) sowings at Gunung Medan, respectively. In contrast, the October (wet) and February (moderately wet) sowings gave the highest and lowest indices at Sitiung, respectively. Significant T x S interaction on panicle blast was also obtained at Sitiung ($P= 0.0001$). Analysis of such interaction with linear contrast showed, however, that all temperature-sowing combinations gave insignificantly different panicle blast indices among observations at Sitiung ($P > 0.05$) except if a zero or one degree increase in temperature occurs either in February (moderately wet) or October (wet) ($P < 0.001$).

DISCUSSION

In most cases, disease forecasting is limited by the availability of disease and weather databases from which models can be generated. Several procedures, both empirical and mechanistic in nature, can be used to extrapolate missing observations necessary to complete the weather database. A common practice is to get information from sites adjacent to the target location where values are averaged, or use a smoothing spline method as an interpolation technique (Hutchinson, 1991).

The use of a weather generator, SIMMETEO (Geng et al., 1988) in this study allowed generation of daily weather observations from monthly means. With other statistical techniques such as regression, time series, and discriminant analyses, daily values were extracted for variables in areas where daily data were not available. Comparisons of monthly values of actual (available information) with simulation (Fig. II.4a-c) have shown agreement, and the fluctuation of values around the mean of simulated variables (± standard deviations) (Fig. II.5a on rainfall and wind speed; Figs. II.5b-c) showed an acceptable range of values.

SIMMETEO generates rainfall based on a two-state first-order Markov chain and a two-parameter gamma probability function which allows identification of a certain day as either dry or wet (Geng et al., 1988). Temperature and radiation, on the other hand, are described as conditional multivariate normal random variables determined by the rainfall status of the day (Richardson and Wright, 1984). Wind speed can be either a two-parameter Gamma (locations with rare strong winds) or a Weibull distribution (locations with variable wind speeds and winds over 10 m/s). Relative humidity is calculated as a direct function of temperature and vapor pressure (Goudriaan, 1977). The SIMMETEO program had been tested to generate values at two different locations (see Materials and Methods) and had shown agreement with long-term fluctuations in weather (Geng et al., 1985a, 1985b). Thus, it can be fitted to extrapolate values of missing rainfall and wind speed information at Icheon, South Korea, a temperate rice area, and to generate the entire database for Gunung Medan and Sitiung in Indonesia, which are tropical regions. It is important to note, however, that since no actual daily values were available from the Indonesia sites to test the validity of simulation, predictive models developed from these sites could produce incorrect conclusions about blast. Hence, the readers are reminded that the results from the models at Gunung Medan and Sitiung should be interpreted with caution.

Models III, V, V, II, II were judged as the best models for maximum lesions at N level of 110 kgN/ha, maximum lesions at 220 kgN/ha, final lesions at 110 kgN/ha, final lesions at 220 kgN/ha, and panicle blast incidence at 220 kg/ha, respectively at Icheon (Table II.5a). Only one model was generated for panicle blast incidence at 110 kgN/ha.

When combining data sets of two nitrogen (N) levels at the site, models I, II, and V were chosen as best (Table II.5b). Generally, these models describe the positive influence of relative humidity factors that occur immediately prior to or after planting on lesion number regardless of nitrogen (N) level but the negative influence on panicle blast at high N level (Fig. II.6a). Similarly, this relationship has been revealed when N is used as another predictor variable.

It is known in rice blast epidemiology that high humidity favors release of inoculum (Barksdale and Asai, 1961; El Refaei 1977; Ou et al., 1974) and infection (Choi et al., 1988; El Refaei, 1977; Kato, 1974, 1976; Kingsolver et al., 1984; Suzuki, 1975). The important role of saturated air on survival of air-borne conidia has also been reported (Hashioka, 1965; Kapoor and Singh, 1977). Severity of disease during the cropping season is dictated by the density of initial inoculum and success of secondary cycles. A large amount of air-borne *P. grisea* propagules at the start of the season brings about a higher chance of infection. At higher humidity levels, more air-borne inocula survive to initiate infection. Once the process starts, continuous high humid conditions provide greater success in completing a monocycle and continuing into a series of secondary ones. The negative effect of humidity in panicle blast incidence is likely attributed to the fact that no direct relationship exists between leaf and panicle pathosystems, and each may require much different weather conditions (personal communication, Bienvenido Estrada, IRRI). It is likely that the differences in disease occurrence between these two blast pathosystems are linked to phenology-specific adaptations of pathogen races to the cultivar in question (personal communication, Jose Bandong, IRRI).

Total precipitation (TPREC), likewise, positively influences lesion number on leaves and the incidence of panicle blast at low N level at Icheon (Fig. II.6a). The temperature factor, DG25C and a rainfall factor, CDWOP had negative influences on lesion numbers regardless of nitrogen level (Fig. II.6a). The positive relationship shown by rainfall on leaf and panicle blast is attributed to dispersion of propagules (Koizumi and Kato, 1991; Nakamura, 1971), in addition to providing free moisture in plant parts. This latter argument also supports why days without rain (CDWOP) caused less disease. In South Korea, Kim and Kim (1991) reported that an increase in air-borne spores immediately after rain provided direct indications of potential blast build-up. Rainfall beyond 83 mm/day, however, may wash off spores from host tissues and air and could consequently cause less infection (Suzuki, 1975); such a negative relationship is shown in the panicle blast model V with rainfall factor, DR84 (number of days with rainfall above 83 mm/day) (Table II.5b). The factors DG25C and DOPT occurred several days before planting and had negative effects on leaf blast at this site probably because overwintered inoculum are vulnerable to high temperature in temperate conditions. Hashioka (1965) reported that the conidia of the temperate blast fungus are less resistant to heat than to cold. An increase in temperature, therefore, reduces the viability of air-borne spores (El Refaei, 1977; Hashioka, 1965). Such a reduction in viability leaves less chance for the pathogen to infect host tissues, thereby reducing the number of lesion produced on the leaves.

Positive nitrogen effects on blast are well documented (Beier et al., 1959; El Refaei, 1977; KÜrschner et al., 1990; Paik, 1975; Sakamoto, 1948) and were evident not only in the Icheon models but also in the Cavinti models (Fig. II.6b). Although, N amount gave insignificant regression coefficients at the latter site (Table II.5c-d), its biological importance to blast development has been proven. Physiologically, epidermal cells tend to collapse with high N, increasing water permeability. Ito and Sakamoto (1943) and Sakamoto (1948) demonstrated that host resistance decreases with increased water permeability of epidermal cells.

Based on meteorological factors included as predictors, models generated for blast on IR50 differed from those for C22. Models V, III, and V were judged as best models at Cavinti predicting maximum DLA, final DLA, and panicle blast severity, respectively, on IR50 (Table II.5c). These models consistently had the wind speed factor, DWS35 as a predictor. The IR50 models also included MMAX, MRH, and

PFREQ in a few cases. Models IV, III, and V, on the other hand, were chosen to predict maximum DLA, final DLA, and panicle blast severity on C22 (Table II.5d), respectively. These models had mostly rainfall factors such as PFREQ, CDWP, and TPREC; temperature factor, MMIN; and solar radiation factor, MSR as predictors. Such a discrepancy between the cultivars in weather requirements for blast severity may have two reasons: first, the predisposition of plants by the type of conditions they were planted in, and second, the subsequent effect of weather on the population of *P. grisea*. Experiments at Cavinti were conducted under upland conditions. Although, both cultivars showed susceptible reaction to blast, IR50, a lowland cultivar, is not suited to these conditions and thus, was disposed to severe pathogen pressure. On the other hand, C22, being an upland cultivar, is more adapted to such an ecosystem and maybe made it less disposed to attack by the pathogen.

IR50 and C22 have been found to harbor different *P. grisea* lineages in order for the disease to develop (Dahu, 1993). Dominant lineages of *P. grisea* found at Cavinti infect both IR50 and C22 (Dahu, 1993). Low initial disease scores on C22 and consistent high scores on IR50 across the years (Fig II.3b), however, suggest that lineages attacking IR50 might have dominated the area originally (Dahu, 1993). It can be seen from disease and weather patterns during 1993 that high disease was recorded on C22 only in the June 1993 sowing, even though no drastic change in weather patterns was observed from June onwards in 1992 and 1993 except for wind speed (Fig. II.7a). With regard to IR50, variations in severity were shown only by panicle blast but not by leaf blast (Fig. II.1b). The build-up of lineages attacking C22 can be attributed to the repeated sowings of this cultivar which exerted selection pressure on pathogen populations. This type of phenomenon has been referred to as the "boom and bust" cycle (Palti and Kranz, 1980).

In general, at Cavinti, wind speed (DWS35), maximum temperature (MMAX), rainfall (PFREQ) gave negative effects to leaf blast; PFREQ and TPREC were negatively correlated with panicle blast. Factors such as MRH, MSR, and CDWP were positively correlated with both leaf and panicle blast. The relationships support what is known about the epidemiology of blast. Strong winds beyond 3.4 m/s bring about low disease because spores are blown to longer distances and not retained within the canopy (Suzuki, 1975). On the other hand, increased maximum temperature in the tropics brings about non-optimum conditions for several stages of the pathogen life cycle (El Refaei, 1977). The rainfall effect contrasts what has been observed at Icheon probably because heavy rainfall is experienced more at Cavinti (Fig II.7a) than at Icheon (Fig II.5a) during rice growing months. Washing-off of spores on the leaves and in the air caused by heavy downpour reduces the chance of blast occurrence and is most probable at Cavinti. With regard to solar radiation, its effect on disease on C22 is tied with the effect of the rainfall factor, CDWP, as given by a VIF value greater than two (Table II.5d). This shared effect (multicollinearity) demonstrates that days with rainfall beginning 20 DBS are necessary to provide enough moisture for inoculum survival when host tissues are not available. The radiation effect has not been well studied in blast epidemiology, but it has been proposed that sporulation is affected (Calvero et al., 1994).

Models IV and V were chosen to predict final DLA and panicle blast severity, respectively, at the IRRI blast nursery. The low correlation of weather factors generated low adjusted-R^2, low ACC values, and over 25% CV (Table II.5e). The relatively inferior test statistics of the IRRI models compared to the other sites used were attributed to the way disease developed at the nursery. Several other plots sown with blast-infected spreader rows were adjacent to the test plots actually used in the experiment. The continuous flow of inoculum coming from the spreader rows all year round made blast development artificial rather than natural. Because of this, the influence of weather on blast development and progression became negligible, with severe infection produced even under unfavorable conditions. In this effect, there was no linear relationship existed between weather factors and disease, yielding low test statistic values in the analysis.

At the nursery, the number of days with maximum temperature greater than 25 C (DG25C) had positive influence on both leaf and panicle blast (Table II.5e). On the other hand, MRH and CDWOP had positive and negative influences on panicle and leaf blast, respectively (Table II.5e). The positive influence of DG25C on blast is somewhat biologically incorrect if its effect is directly linked to the life stages of *P. grisea*. Based from previous studies, high temperature is unfavorable to disease because it inhibits sporulation or slows down the infection rate (Chiba, et al., 1972; El Refaei, 1977; Hashioka, 1965; Kato, 1974, 1976; Kim and Yoshino, 1987; Kingsolver et al., 1984; Suzuki, 1975; Yoshino, 1972). However, increase in temperature also predisposes the host to pathogen attack and may produce susceptible reaction (Veeraghavan, 1982). At the nursery, maximum temperature was always above 25 C during the 1989-1992 experiment (Fig. II.7b). Such an occurrence of maximum temperature ranges at the nursery would easily predispose IR50 cultivar to blast infection.

Although insignificant, MRH was included in the IRRI panicle blast models for two reasons: a single predictor would be insufficient to explain the pathosystem involved, and inclusion of MRH in models would be biologically justifiable. The choice of the two-predictor models for panicle blast was based on the fact that the pathosystem is a complex system that consists of several interacting environmental factors. Even so, the temperature factor, DG25C and three humidity factors (MRH, DRH80, CDRH80) were the only ones found correlated with panicle blast. From

WINDOW PANE analysis, although MRH had low correlation with panicle blast, it was not multicollinear with DG25C, a significant predictor in the model. Multicollinearity does not actually affect the predictive ability of regression models (Myers, 1990; Neter et al., 1989), but adding CDRH80 and DRH80 would tend to mask the real influence of MRH and DG25C on the response variable.

Model III at Gunung Medan was the best model for estimating panicle blast index (Table II.5f). At Sitiung, model I was found appropriate for predicting both leaf and panicle blast (Table II.5g). The best model at Gunung Medan gave CDWP positively related to panicle blast, while the maximum temperature factor, DG25C was related negatively to the same parameter at Sitiung. Total precipitation (TPREC) also appeared to negatively affect leaf blast at Sitiung.

Disease differences between the two sites are apparent because of differences in weather patterns during the years blast occurred even though the sites are adjacent to each other. There are two possible reasons for these differences: 1) there were only two years weather data available at each site with only one year the same for both (Figs. II.5b-c); and 2) there was an effect of altitude with Sitiung being at higher elevation than Gunung Medan (personal communication, Paul S. Teng, IRRI). The values of mean temperature, total rainfall, solar radiation, and humidity were higher at Gunung Medan than at Sitiung. Even so, disease values were higher at the latter site than at the former (Fig. II.1d).

The pattern of disease appeared to be affected more by rainfall and humidity (vapor pressure) than by solar radiation and temperature at both sites (Figs. II.5b-c). Unfortunately, humidity was not included in the models because of the limitation of few sample size. Although statistically valid, the Indonesia models would not estimate blast severity accurately because only a single weather factor explains the complexity of the pathosystem. Similarly, models developed from simulated weather databases as in the case of the Indonesia sites, will not always warrant correct estimates of the disease. Because of the unavailability of the weather data, the Indonesia models should be further investigated to develop a solid argument on the validity of the weather extrapolation techniques used and on the applicability of the predictive models.

Exploring model performance using simulated weather data under hypothetical increases in temperature is appropriate in identifying key issues about the effects of global warming on blast epidemics. From model estimates of blast, it was shown that increases in temperature affect disease differently in different situations. A panicle blast outbreak would be possible at Icheon with an increase in temperature. At Cavinti, a severe leaf blast infection could be possible under warmer conditions on C22. Regardless of temperature, the IR50 cultivar appeared to be always susceptible to blast at Cavinti. A shift to high temperatures at the IRRI blast nursery and the Indonesia sites would not cause any severe blast outbreak. Although the disease trends at the sites are logical from the models, drawing firm conclusions from such a procedure is speculative. Real experiments should be carried out under controlled environments to substantiate the trends produced from the models. Actual blast surveys to determine the intensity of disease at these locations should also be done to support if models estimated the disease as expected. This type of work (Luo et al., 1993) was recently applied to BLASTSIM.2, a simulation model for tropical rice-blast pathosystem (Calvero et al., 1994; Teng and Calvero, 1991). For this, the Geographic Information Systems (GIS) were used to superimpose the effect of UV-B (ultraviolet-beta) radiation on BLASTSIM.2-generated blast progressions converted into the area under the disease progress curve (AUDPC) units (Luo et al., 1993). The GIS-generated raster maps of several Asian countries showing the possible blast hot-spot areas were then compared with actual blast incidence at those sites. The results showed that the BLASTSIM.2 model simulated the expected locations of blast-prone areas in these tropical and temperate Asian countries (Luo et al., 1993; personal communication, Paul S. Teng, IRRI).

The WINDOW PANE program identified the environments correlated with blast at some key sites in Asia and generated information as to how these factors are associated with disease. Discrepancies in the relationships between disease and the environment at different sites or for different cultivars are attributed in part to the fact that different races of *P. grisea* occur in these sites. The type of environment may affect site-specific adaptation of these races and may characterize the kind of climatic conditions required to have epidemics. In addition, models generated from the sites warrant further verification and if new observations are obtained, should be reexamined. Models that were generated from small data sets like those from Sitiung, Gunung Medan, and Cavinti are inferior and may predict dubious disease values. Likewise, models developed from simulated weather databases, such as those in Indonesia, should not be used to derive inferences about blast in these sites because of the uncertainty of the generated values.

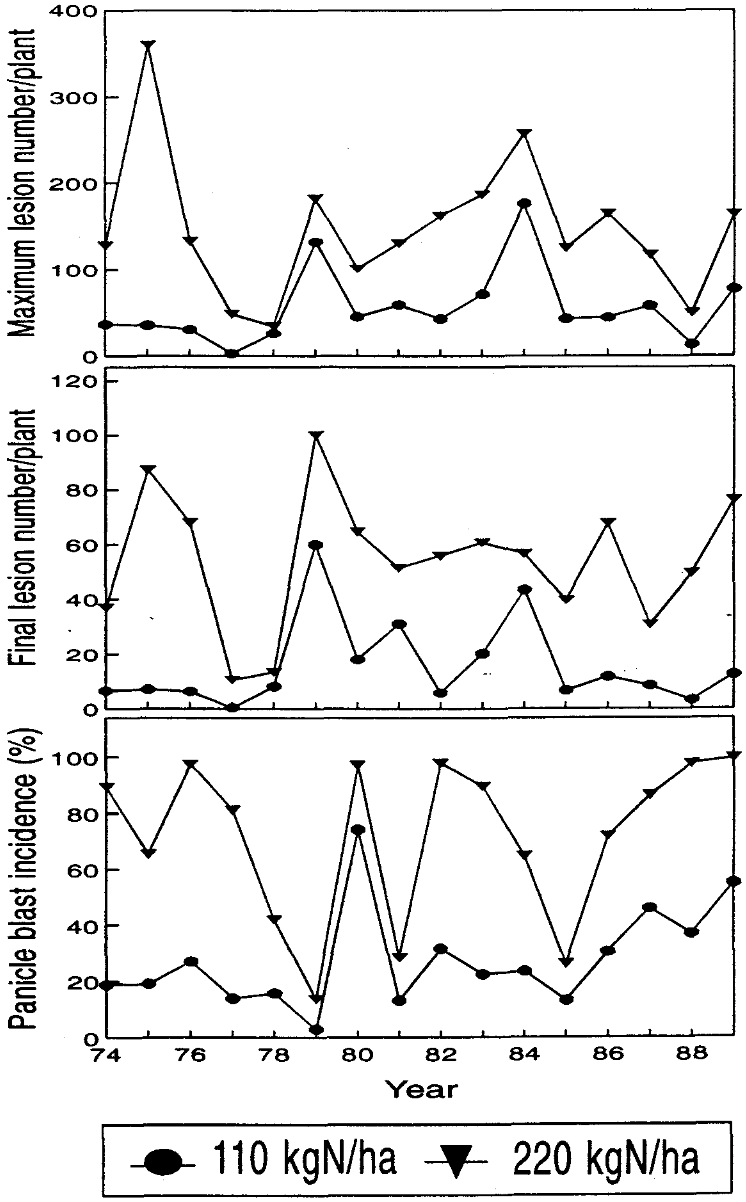

Fig. II.1a. Rice blast parameters on Jin heung cultivar at Icheon, South Korea during 1974-1989 (data courtesy of Dr. C.K. Kim, RDA, Suweon, South Korea).

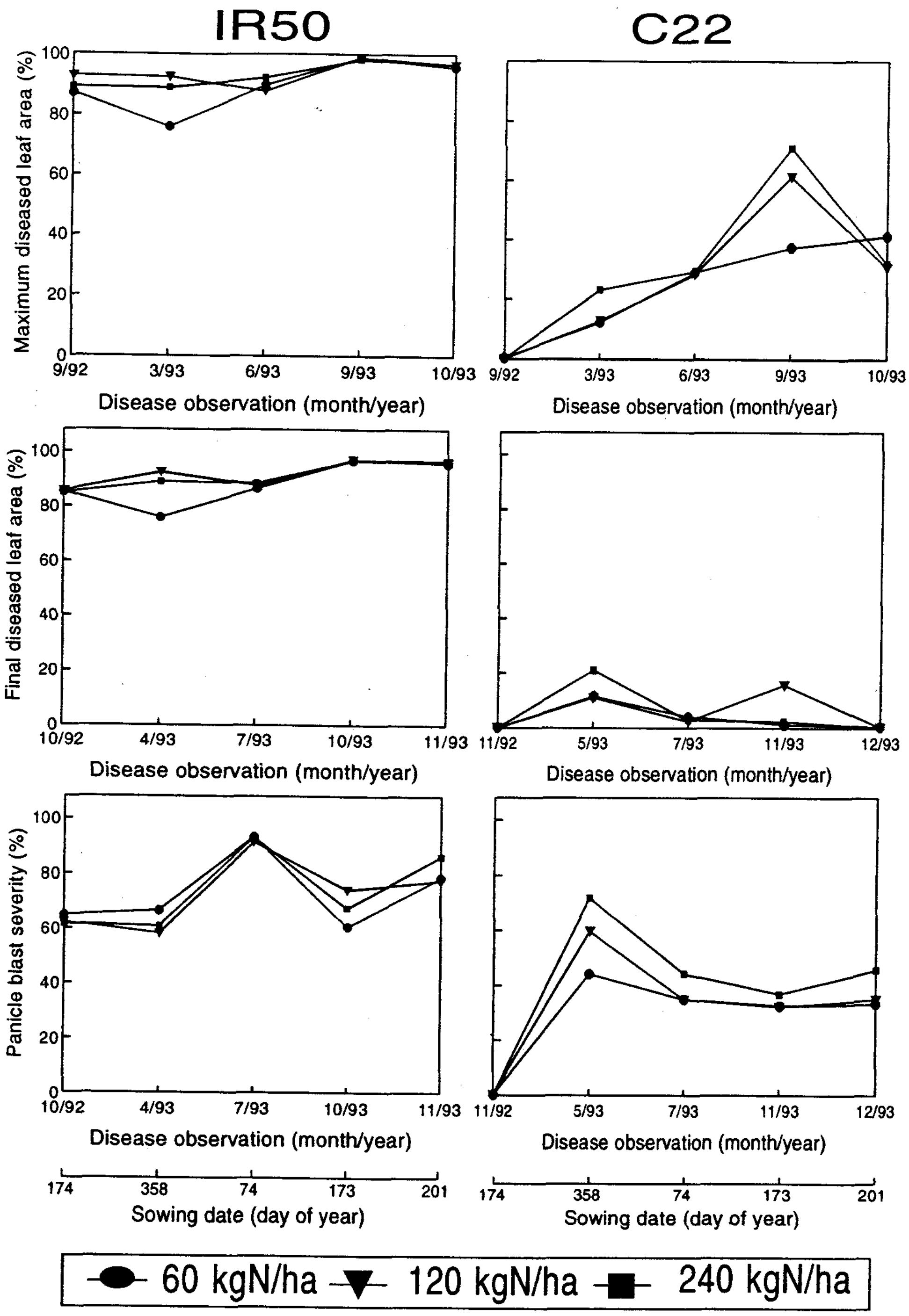

Fig. II.1b. Rice blast parameters on IR50 and C22 cultivars at Cavinti, Philippines during 1992-1993 under three nitrogen treatments.

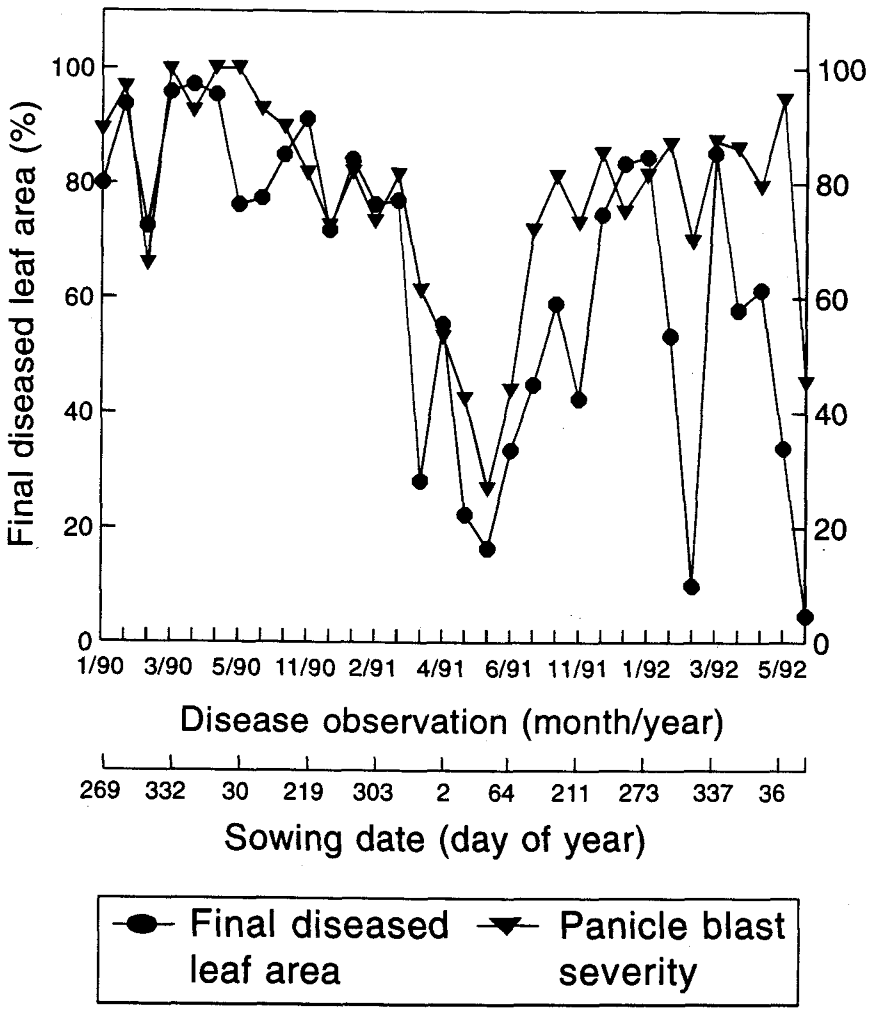

Fig. II.1c. Rice blast parameters on IR50 cultivar at the IRRI blast nursery, Philippines during 1989-1992.

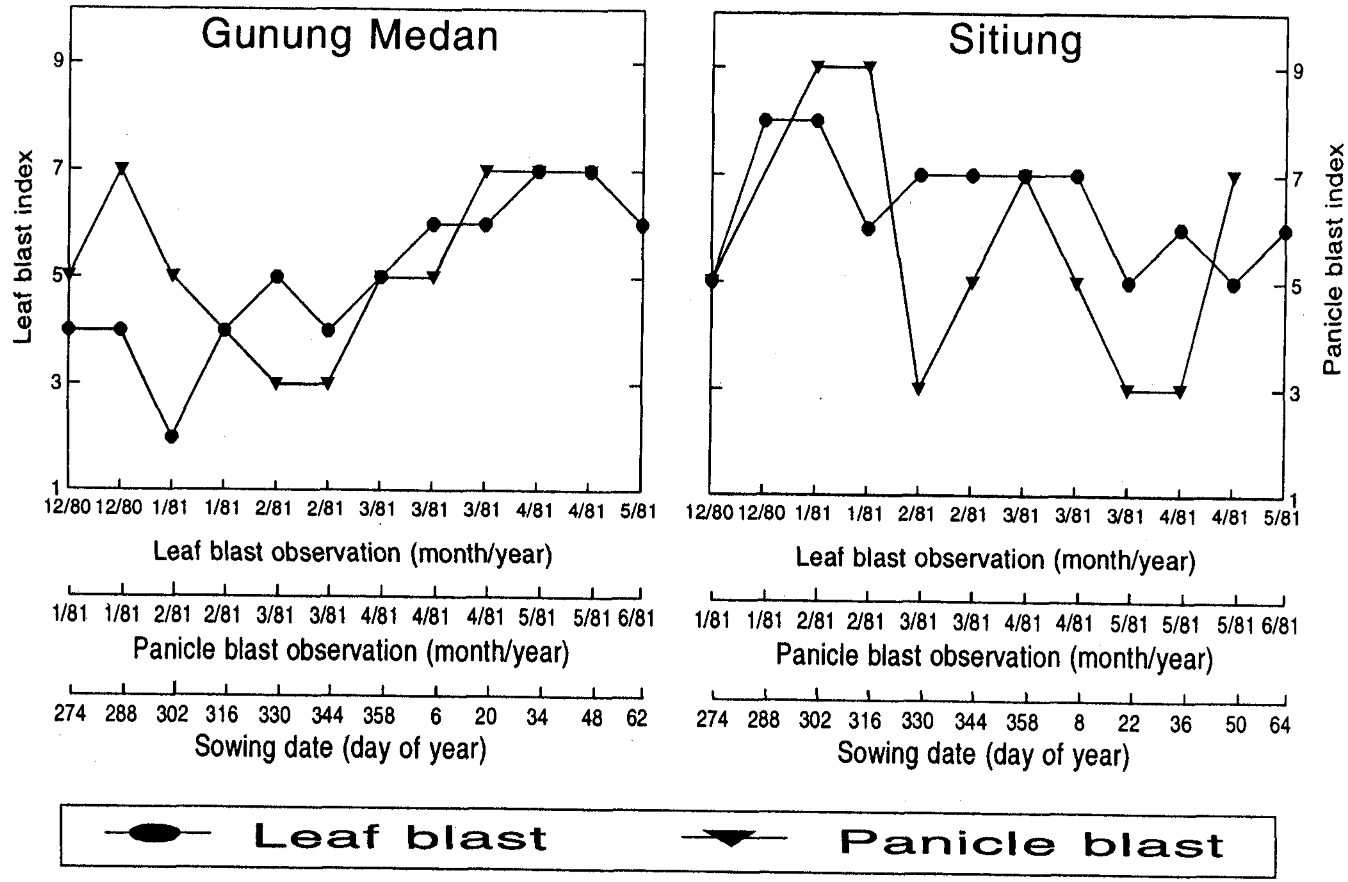

Fig. II.1d. Rice blast parameters on C22 cultivar at Gunung Medan and Sitiung, West Sumatra, Indonesia during 1980-1981 and 1981-1982, respectively (data courtesy of S. Darwis, SARIF, Indonesia).

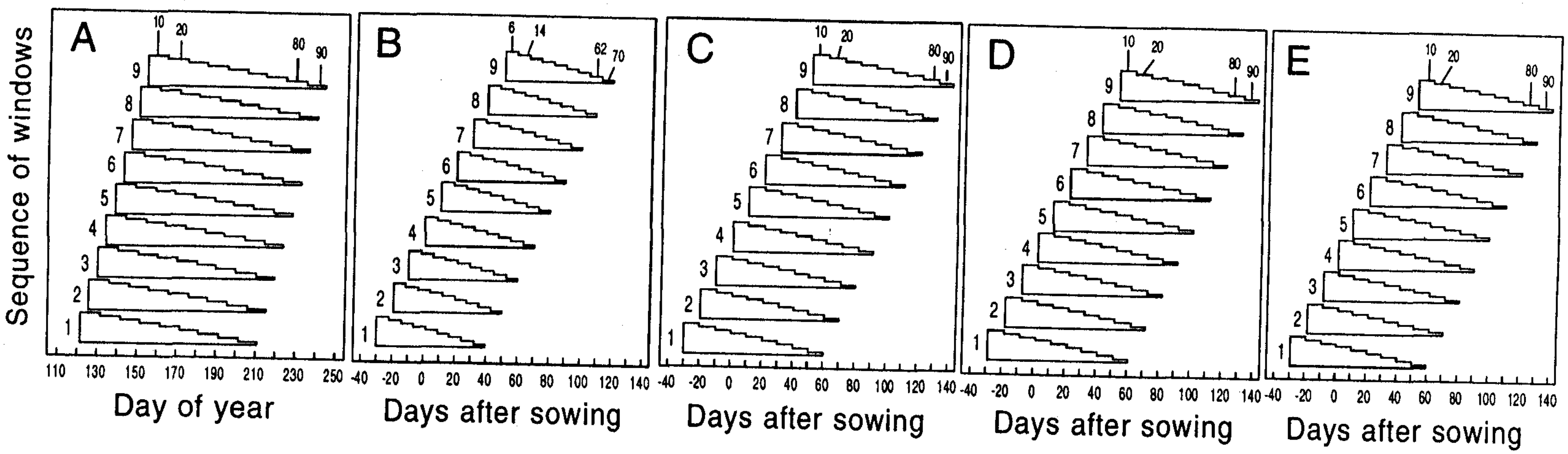

Fig. II.2. Sequence of windows showing how WINDOW PANE program generated meteorological factors for developing predictive models for **A**, Icheon, South Korea, **B**, Cavinti and **C** , IRRI blast nursery, Philippines, and **D**, Gunung Medan and **E**, Sitiung, West Sumatra, Indonesia. There are 9 window sets each having smaller subsets; e.g. window set 1 at Icheon started at DY 121 and moves four days forward to start at DY 125 for window set 2. Each set has 10 and 90 days duration for shortest and longest subsets, respectively, at this site.

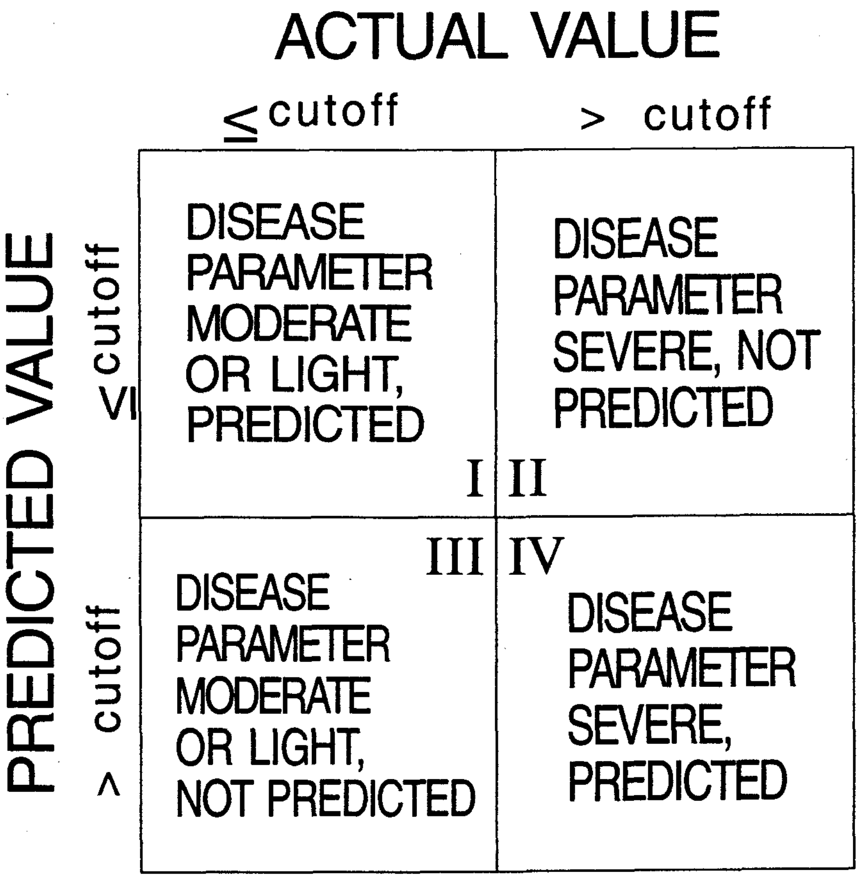

Fig. II.3. Contingency quadrant used to determine the accuracy (ACC) of disease prediction relative to actual disease value. In quadrants I and IV, actual and predicted values are in agreement. In quadrants II and III, under and overprediction occur. Cutoff points are presented in Table II.3.

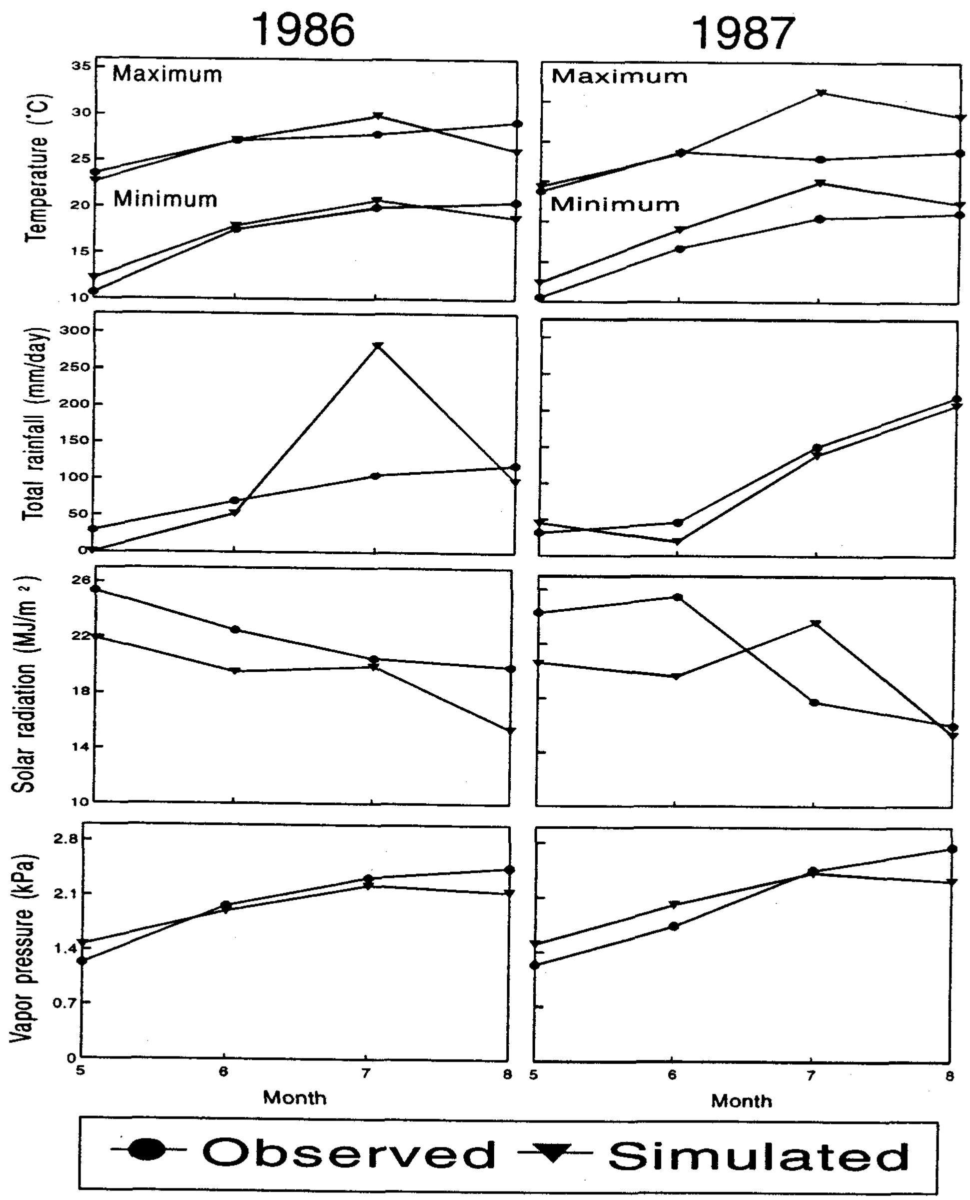

Fig. II.4a. Trends of observed and simulated meteorological variables at Icheon, South Korea during 1986-1987. The weather data base has daily values from May to August only. Missing observations of rainfall and wind speed also exist in 1986-1989. Simulation was done by SIMMETEO (Geng et al., 1988) to fill in missing observations.

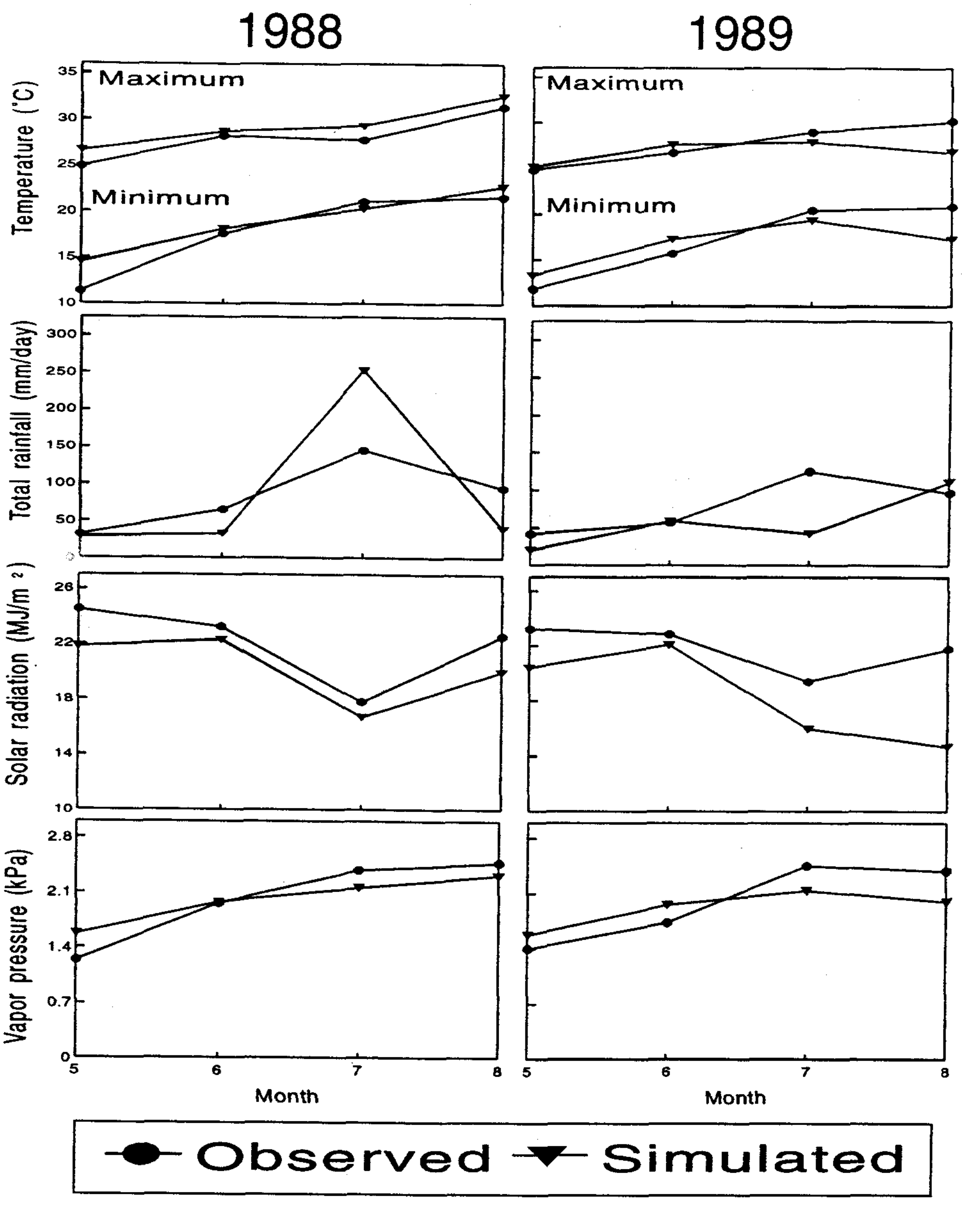

Fig. II.4b. Trends of observed and simulated meteorological variables at Icheon, South Korea during 1988-1989. The weather data base has daily values from May to August only. Missing observations of rainfall and wind speed also exist in 1986-1989. Simulation was done by SIMMETEO (Geng et al., 1988) to fill in missing observations.

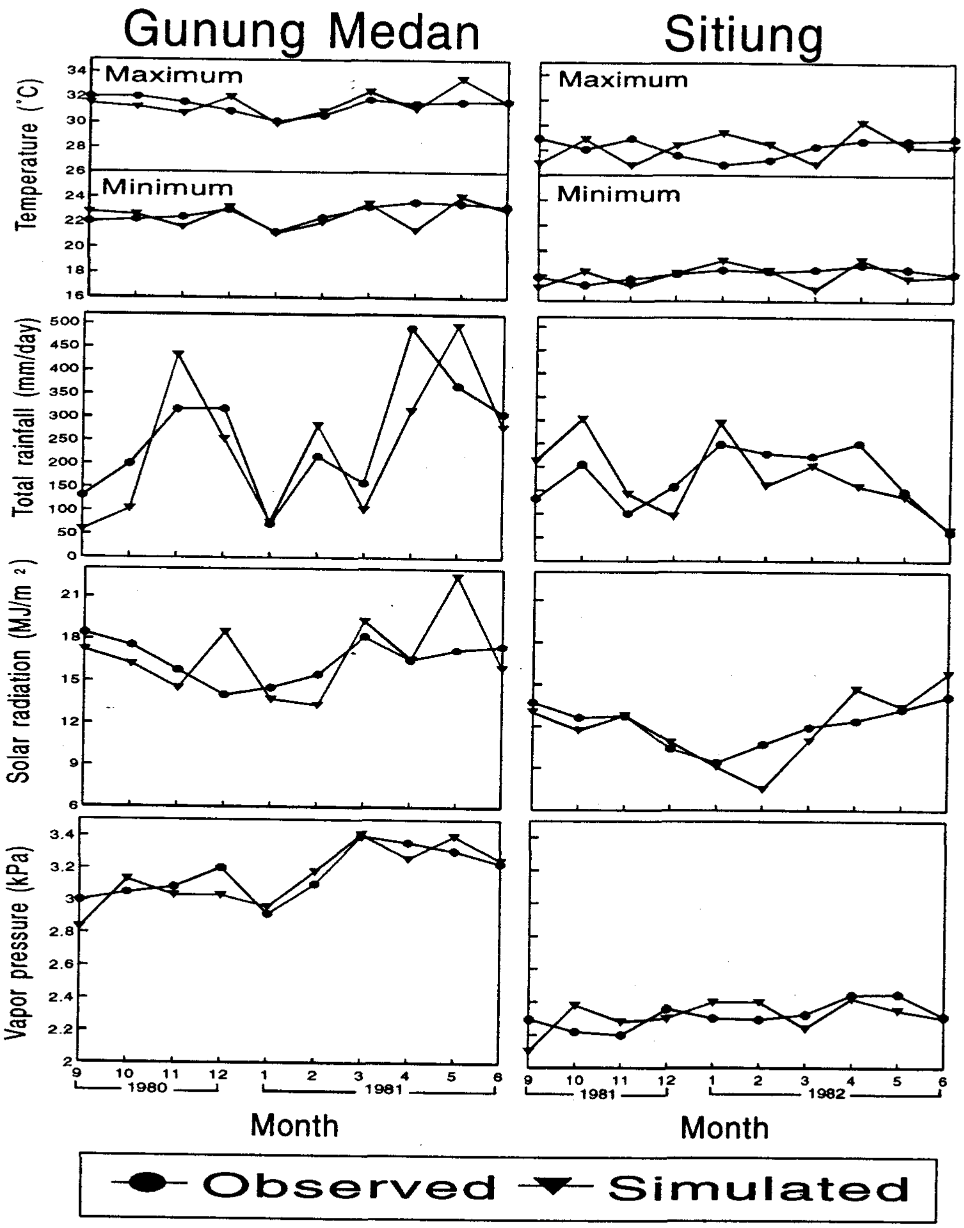

Fig. II.4c. Trends of observed and simulated meteorological variables at Gunung Medan and Sitiung, West Sumatra, Indonesia during 1980-1981 and 1981-1982, respectively. Daily values of weather data base used by WINDOW PANE program were entirely simulated using SIMMETEO (Geng et al., 1988).

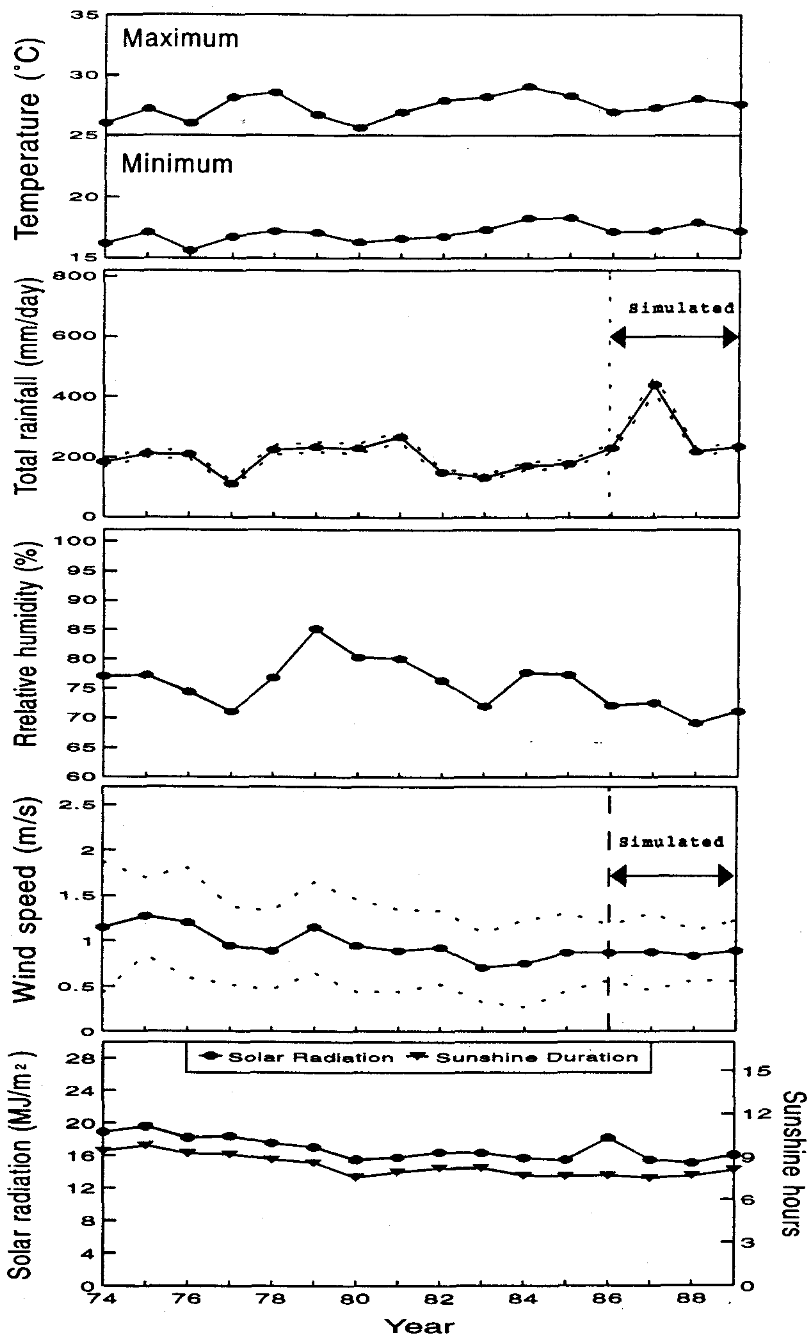

Fig. II.5a. Monthly mean values of weather variables at Icheon, South Korea during 1974-1989 with rainfall and wind speed simulated in 1986-1989 (broken lines). Dotted lines are mean values of simulated variables ± standard deviation.

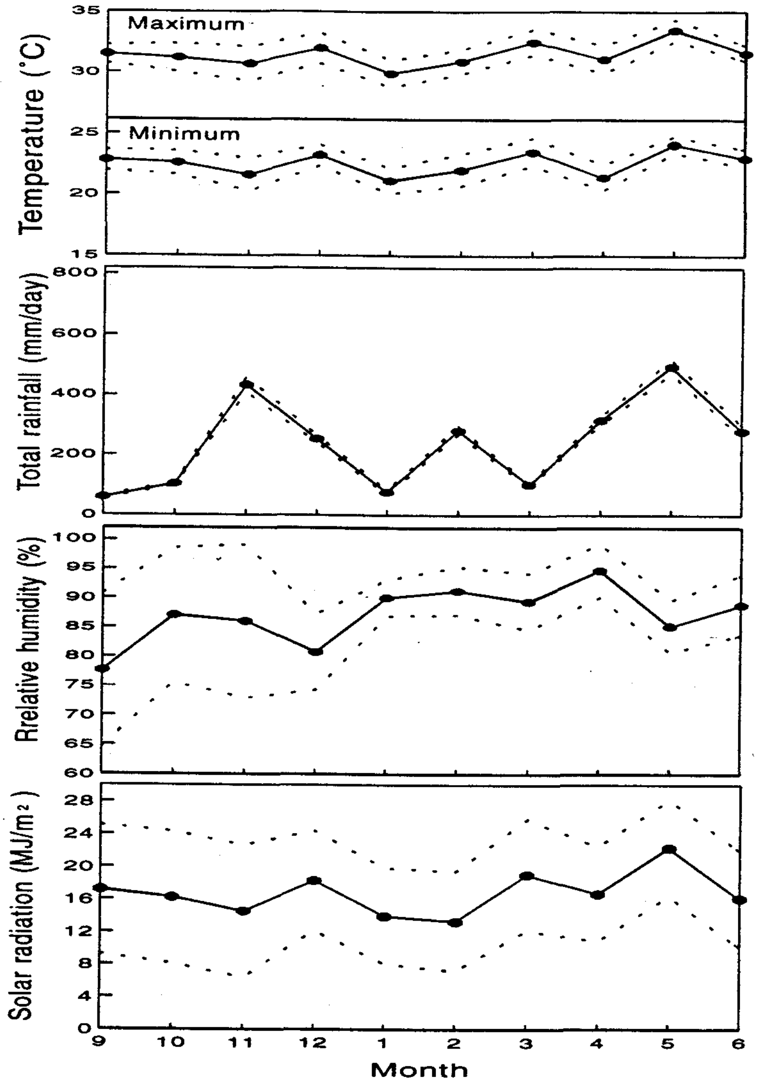

Fig. II.5b. Monthly mean values of weather variables at Gunung Medan, West Sumatra, Indonesia during September 1980 to June 1981. Daily values were entirely simulated by the SIMMETEO program. Dotted lines are monthly values of variables ± standard deviation.

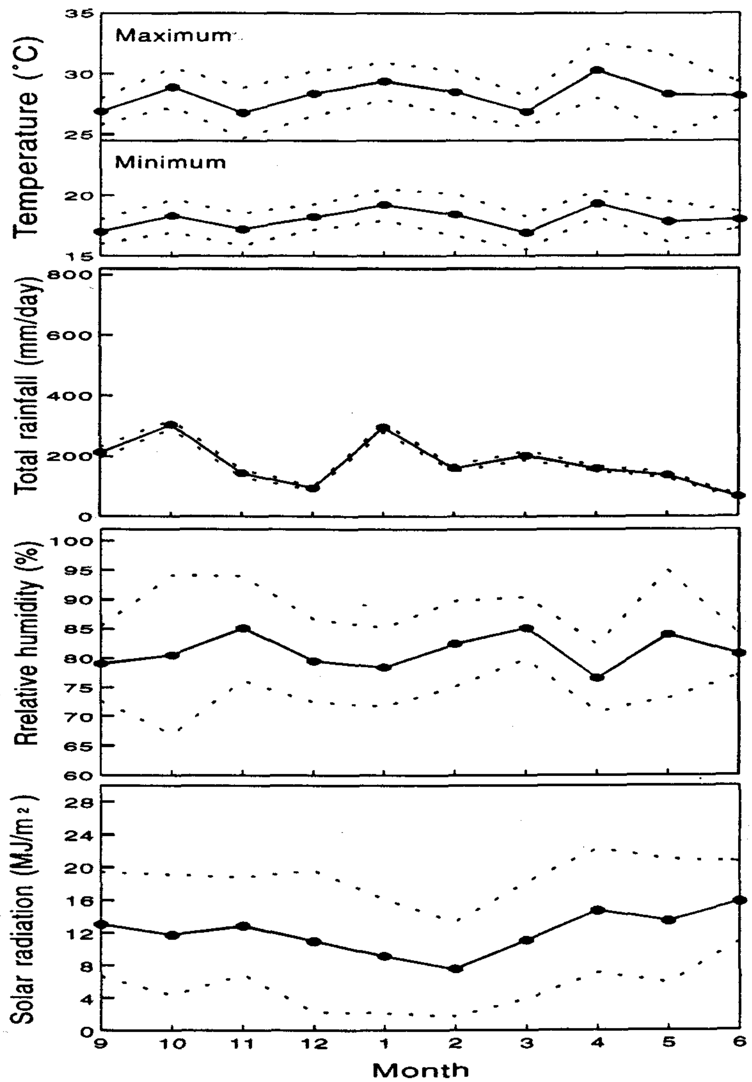

Fig. II.5c. Monthly mean values of weather variables at Sitiung, West Sumatra, Indonesia during September 1981 to June 1982. Daily values were entirely simulated by the SIMMETEO program. Dotted lines are monthly values of variables ± standard deviation.

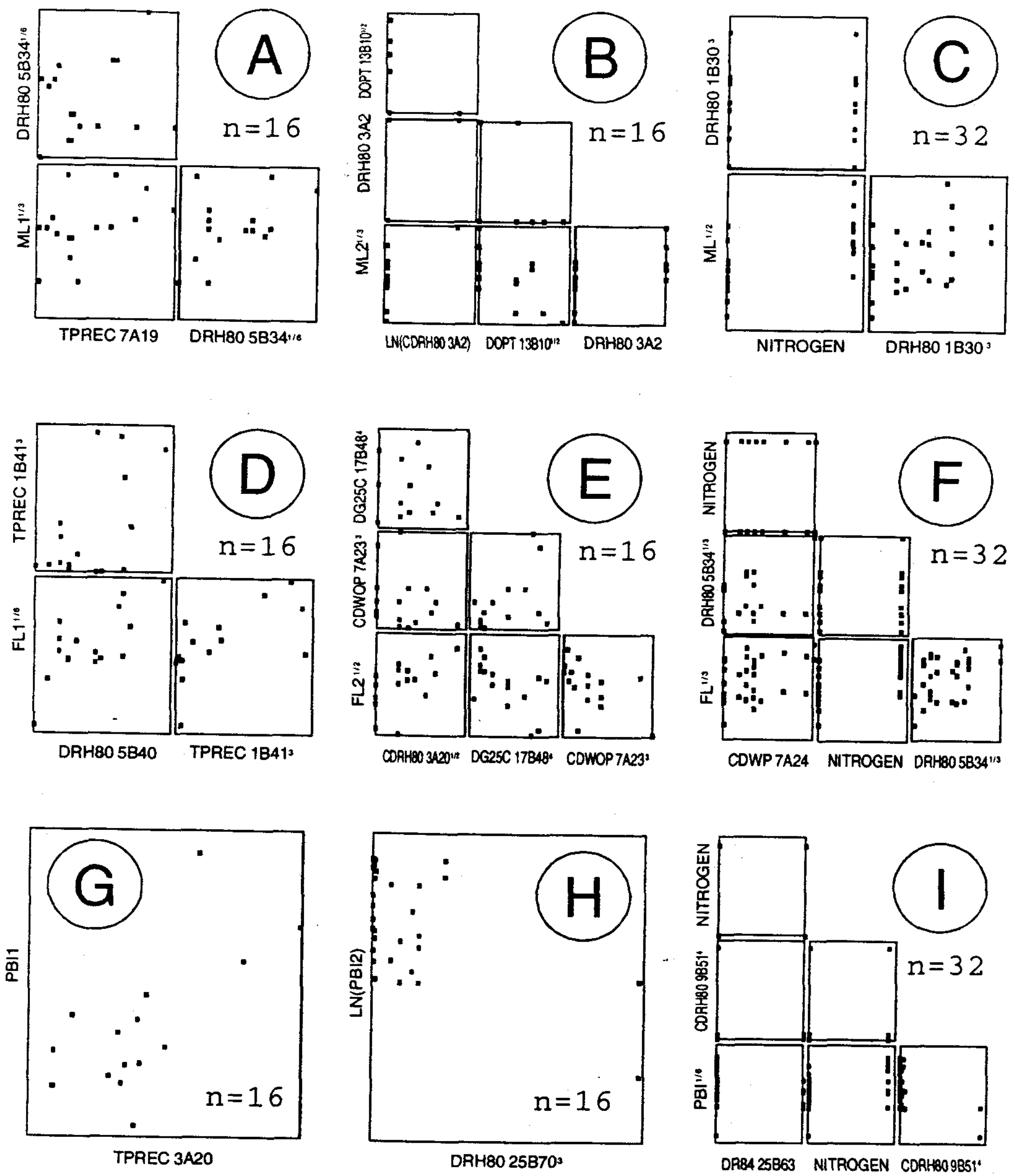

Fig. II.6a. Scatter plots of response (disease parameters) and predictor (weather factors) variables of the models selected that best predict blast at Icheon, South Korea. Plots for maximum lesion number (ML) are A (at 110 kgN/ha), B (at 220 kgN/ha) and C (combined datasets). Plots for final lesion number (FL) are D (at 110 kgN/ha), E (at 220 kgN/ha), and F (combined). Plots for panicle blast incidence (PBI) are G (at 110 kgN/ha), H (at 220 kgN/ha), and I (combined). Descriptions of weather factors are presented in Table II.3. Descriptions of factor durations are presented in footnotes of Tables II.5a-b.

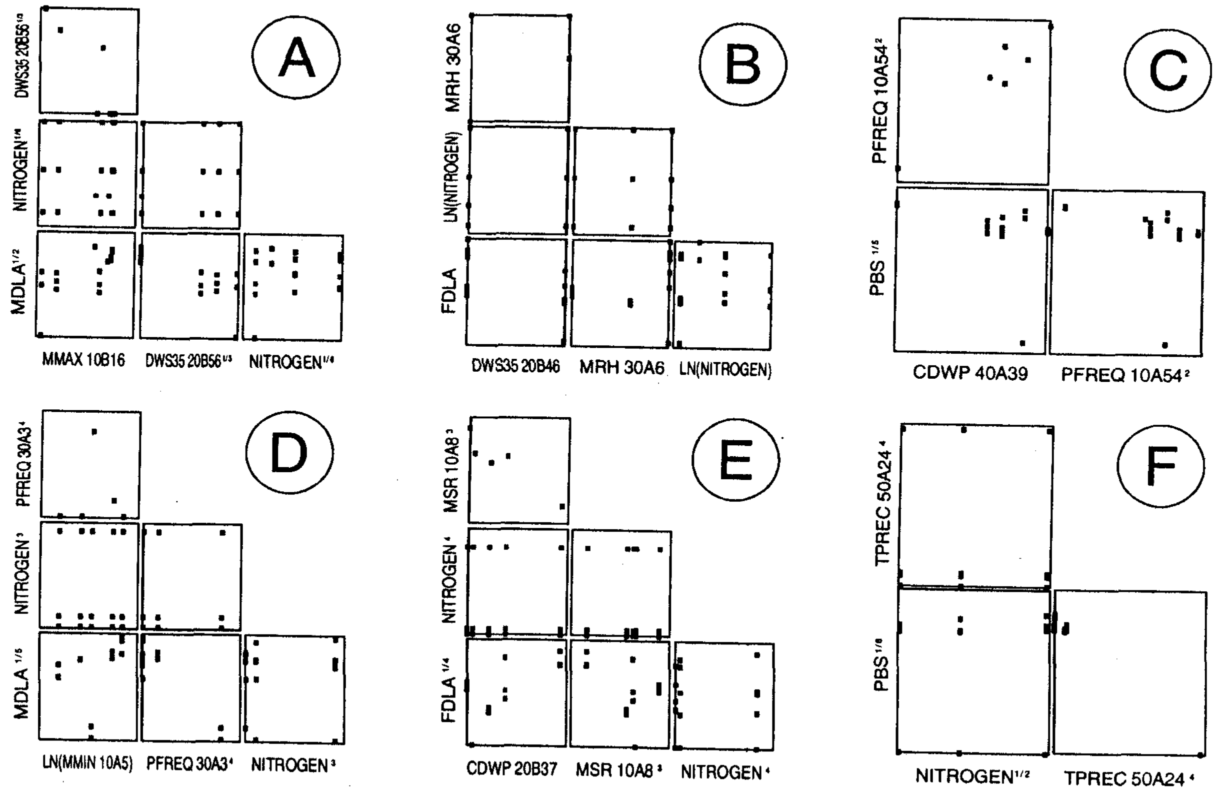

Fig. II.6b. Scatter plots of response (disease parameters) and predictor (weather factors) variables of the models selected that best predict blast on IR50 and C22 cultivars at Cavinti, Philippines. Plots for maximum diseased leaf area (MDLA), final DLA (FDLA), and panicle blast severity (PBS) on IR50 are A, B, and C, respectively. Plots for maximum DLA, final DLA, and panicle blast severity on C22 are D, E, and F, respectively. Descriptions of weather factors are presented in Table II.3. Descriptions of factor durations are presented in footnotes of Tables II.5c-d. Number of observations is n= 17.

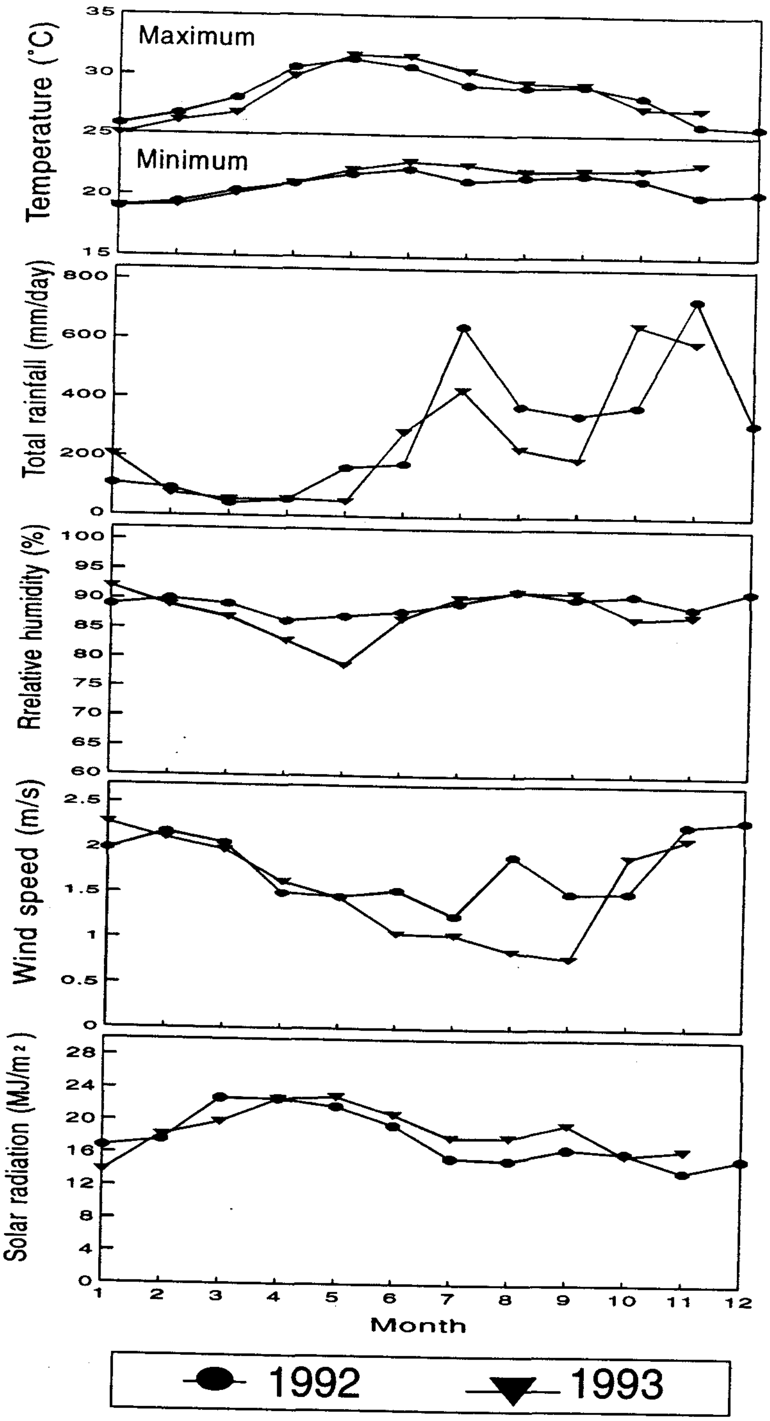

Fig. II.7a. Monthly mean values of weather variables at Cavinti, Laguna, Philippines during 1992-1993.

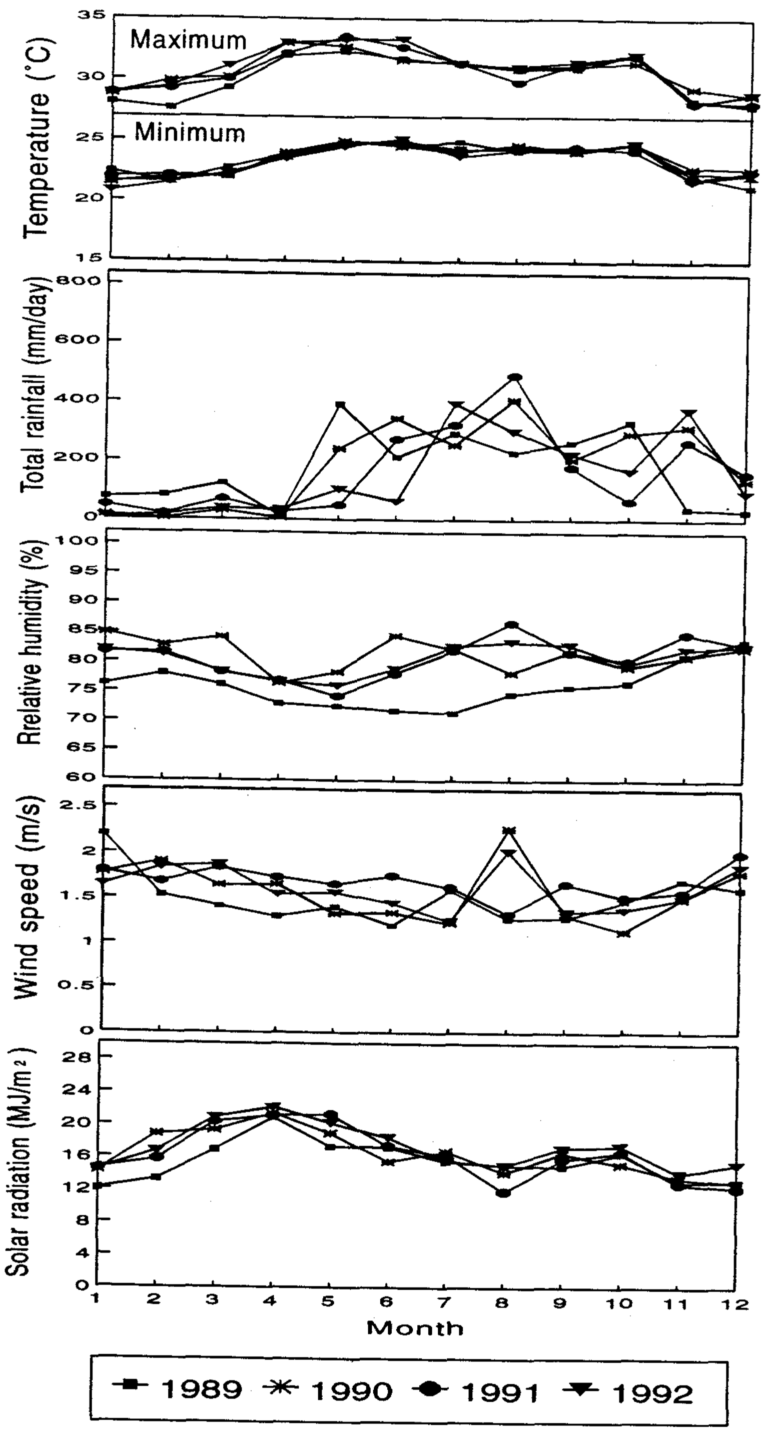

Fig. II.7b. Monthly mean values of weather variables at the IRRI blast nursery, Philippines during 1989-1992.

Table II.1a. Coefficient values of weather variables used by SIMMETEO as input data to extrapolate daily rainfall and wind speed for 1986-1989 at Icheon, South Korea.

		Weather variables[a]							
Year	Month	FWD	RPWD	TMAX	TMIN	SOLAR	SUND	VP	WS
1986	May	0.121	7.743	23.568	10.681	25.339	9.294	1.228	1.846
	June	0.276	8.380	27.123	17.477	22.487	7.770	1.965	1.730
	July	0.342	9.878	27.874	19.903	20.474	6.813	2.324	1.710
	August	0.334	11.490	29.258	20.503	19.890	6.826	2.453	1.534
1987	May	0.125	8.218	23.758	10.545	24.303	8.816	1.232	1.855
	June	0.162	9.457	28.697	16.653	25.480	9.253	1.733	1.543
	July	0.385	12.625	27.990	20.490	17.774	5.926	2.451	1.611
	August	0.442	15.997	28.861	21.084	16.019	5.981	2.743	1.285
1988	May	0.104	9.797	24.861	11.339	24.487	8.668	1.235	1.844
	June	0.246	8.789	27.140	17.560	23.223	8.253	1.961	1.613
	July	0.368	12.712	27.758	21.055	17.790	5.313	2.381	1.829
	August	0.243	12.468	31.403	21.565	22.577	8.348	2.473	1.281
1989	May	0.174	7.654	24.758	11.806	23.213	8.519	1.397	1.774
	June	0.230	8.251	26.703	15.680	22.850	8.400	1.735	1.651
	July	0.347	11.644	28.974	20.448	19.419	6.629	2.456	1.553
	August	0.277	11.218	30.184	20.839	21.777	8.694	2.393	1.262

[a]FWD= Fraction of wet days computed as: number of wetdays/total number of days in a month; RPWD= proportion of total rainfall in mm/day per total number of wetdays; TMAX= maximum temperature in C; TMIN= minimum temperature in C; SOLAR= solar radiation in MJ/m^2; SUND= sunshine duration in hours; VP= vapor pressure in kPa; WS= wind speed in m/s.

Table II.1b. Coefficient values of meteorological variables used by SIMMETEO as input data to generate 1980-1981 and 1981-1982 weather data base for Gunung Medan and Sitiung, West Sumatra, Indonesia, respectively.

Site	Month[b]	Weather variables[a]					
		FWD	RPWD	TMAX	TMIN	SOLAR	VP
Gunung Medan	January	0.430	5.330	30.087	21.233	14.529	2.914
	February	0.664	11.215	30.590	23.390	15.493	3.102
	March	0.556	9.232	31.844	23.256	18.174	3.401
	April	0.708	23.132	31.526	23.634	16.535	3.358
	May	0.586	20.252	31.684	23.536	17.240	3.309
	June	0.509	20.219	31.681	23.319	17.521	3.230
	July	0.456	17.761	31.706	22.934	17.870	3.149
	August	0.417	14.705	31.879	22.521	18.340	3.075
	September	0.385	11.334	32.050	22.050	18.408	3.000
	October	0.495	13.043	32.043	22.217	17.539	3.049
	November	0.622	16.990	31.602	22.418	15.763	3.084
	December	0.634	16.179	30.898	23.002	13.997	3.201
Sitiung	January	0.662	11.857	26.864	18.456	9.379	2.302
	February	0.663	12.053	27.270	18.330	10.730	2.294
	March	0.587	12.389	28.356	18.484	11.942	2.324
	April	0.534	15.688	28.812	18.848	12.404	2.442
	May	0.377	12.333	28.814	18.526	13.223	2.448
	June	0.224	8.857	28.958	18.122	14.136	2.312
	July	0.277	9.567	28.892	18.108	14.075	2.305
	August	0.323	10.978	28.877	18.003	13.982	2.300
	September	0.344	13.200	28.944	17.856	13.690	2.292
	October	0.473	13.670	28.087	17.233	12.624	2.219
	November	0.377	9.182	28.959	17.741	12.755	2.199
	December	0.486	10.467	27.604	18.116	10.407	2.359

[a]FWD= Fraction of wet days computed as: number of wetdays/total number of days in a month; RPWD= proportion of total rainfall in mm/day per total number of wetdays; TMAX= maximum temperature in C; TMIN= minimum temperature in C; SOLAR= solar radiation in MJ/m^2; VP= vapor pressure in kPa.

[b]Monthly values in July-August were estimated using Winter seasonal smoothing time series forecasting procedure. Values were used prior to simulation as required by SIMMETEO, but daily simulated values were not included in final data bases.

Table II.2. Meteorological factors considered in generating models for five sites in Asia.[a]

Factor description	Variable Name	Sites				
		Icheon	Cavinti	IRRI	G. Medan	Sitiung
Average maximum temperature (C)	MMAX	x	x	x	x	x
Average mean temperature (C)	MAVE	x	x	x	x	x
Average minimum temperature (C)	MMIN	x	x	x	x	x
Average relative humidity (%)	MRH	x	x	x	x	x
Average solar radiation (MJ/m^2)	MSR	x	x	x	x	x
Average sunshine duration (hours)	MSD	x	o	x	o	o
Average wind speed (m/s)	MWS	x	x	x	o	o
Consecutive days with mean temperature range of 20-27 C	CDOPT	x	x	x	x	x
Consecutive days with precipitation	CDWP	x	x	x	x	x
Consecutive days with relative humidity ≥ 80%	CDRH80	x	x	x	x	x
Consecutive days without precipitation	CDWOP	x	x	x	x	x
Number of days with maximum temperature > 25 C	DG25C	x	x	x	x	x
Number of days with mean temperature range of 20-27 C	DOPT	x	x	x	x	x
Number of days with precipitation ≥ 84 mm/day	DR84	x	x	x	x	x
Number of days with relative humidity ≥ 80%	DRH80	x	x	x	x	x
Number of days with wind speed ≥ 3.5 m/s	DWS35	x	x	x	o	o
Positive degree days with 7 C as base temperature	PDD	x	x	x	x	x
Positive degree days with 10 C as base temperature	PDD10	x	x	x	x	x
Precipitation frequency (days)	PFREQ	x	x	x	x	x
Total precipitation (mm/day)	TPREC	x	x	x	x	x

[a]x= Used in the analysis; o= not used.

Table II.3. Cutoff points used in contingency quadrant to estimate percent accuracy of models developed for rice blast parameters at five sites in Asia.[a]

	Cultivars		
	Jin heung	IR50	C22
Icheon, South Korea			
Maximum lesion number			
110 kgN/ha	55.58	-	-
220 kgN/ha	146.50	-	-
Combined dataset	101.40	-	-
Final lesion number			
110 kgN/ha	15.64	-	-
220 kgN/ha	54.36	-	-
Combined dataset	35.00	-	-
Percent panicle blast incidence			
110 kgN/ha	33.80	-	-
220 kgN/ha	33.80	-	-
Combined dataset	33.80	-	-
Cavinti, Philippines			
Maximum diseased leaf area (%)	-	92.75	27.22
Final diseased leaf area (%)	-	91.22	4.90
Panicle blast severity (%)	-	73.10	33.80
IRRI blast nursery, Philippines			
Final diseased leaf area (%)	-	62.14	-
Panicle blast severity (%)	-	76.99	-
Gunung Medan, Indonesia			
Panicle blast index	-	-	5.40
Sitiung, Indonesia			
Final leaf blast index	-	-	6.42
Panicle blast index	-	-	5.60

[a]Cutoff points were determined from mean values of disease parameters except for panicle blast parameters on Jin heung at Icheon and on C22 at Cavinti which were based on the minimum percentage that can produce 50% yield loss (Torres, 1988). Values falling on quadrants I and IV of the contingency quadrant (Fig. II.3) i.e., both predicted and actual disease parameter values are in agreement, indicate model accuracy.

Table II.4a. Meteorological factors highly correlated with rice blast on Jin heung cultivar at Icheon, South Korea as found by WINDOW PANE program.[a]

Meteorological factor[b]	Beginning date	Time (days)	Correlation coefficient[c]
Maximum lesion number at 110 kgN/ha			
TPREC	7DAT	23	0.58b
	7DAT	19	0.57b
DRH80	5DBT	34	0.62a
	1DBT	30	0.61b
	7DAT	22	0.59b
CDRH80	17DBT	45	0.56b
	1DBT	29	0.59b
	7DAT	21	0.61b
MSD	1DBT	41	-0.53b
	7DAT	21	-0.67a
MSR	7DAT	21	-0.56b
Maximum lesion number at 220 kgN/ha			
DOPT	13DBT	10	-0.53b
	13DBT	9	-0.57b
DRH80	3DAT	10	0.56b
	3DAT	2	0.62b
CDRH80	3DAT	10	0.57b
	3DAT	2	0.71a
Final lesion number at 110 kgN/ha			
TPREC	1DBT	42	0.67a
	1DBT	41	0.68a
DRH80	5DBT	45	0.81
	5DBT	40	0.80
	7DAT	21	0.79
CDRH80	7DAT	32	0.82
	7DAT	21	0.84
MSD	7DAT	25	-0.56b
Final lesion number at 220 kgN/ha			
MMAX	13DBT	52	-0.53b
DG25C	17DBT	48	-0.56b
	7DAT	16	-0.58b
PFREQ	7DAT	28	0.58b
CDWP	7DAT	23	0.59b
CDWOP	1DBT	36	-0.56b
	7DAT	23	-0.57b
DRH80	3DAT	20	0.64a
CDRH80	3DAT	20	0.63a
MRH	3DAT	27	0.57b

Table II.4a. (continued)

Meteorological factor[b]	Beginning date	Time (days)	Correlation coefficient[c]
Panicle blast incidence at 110 kgN/ha			
TPREC	5DBT	30	0.65a
	5DBT	28	0.66a
	1DBT	24	0.68a
	3DAT	21	0.66a
	3DAT	20	0.68a
	7DAT	16	0.64a
Panicle blast incidence at 220 kgN/ha			
TPREC	25DBT	68	-0.70a
DRH80	25DBT	70	-0.76
CDRH80	25DBT	68	-0.79
Combined dataset of 110 and 220 kgN/ha			
Maximum lesion number			
DRH80	9DBT	41	0.38b
	1DBT	30	0.39b
CDRH80	1DBT	26	0.36b
Final lesion number			
CDWP	7DAT	24	0.39b
DRH80	5DBT	34	0.49a
CDRH80	3DAT	26	0.48a
MRH	7DAT	23	0.42b
Panicle blast incidence			
DRH80	25DBT	71	-0.43b
CDRH80	25DBT	70	-0.44b
	9DBT	51	-0.42b
	7DAT	36	-0.42b
MRH	9DBT	61	-0.40b
DR84	25DBT	63	-0.40b

Table II.4a. Footnotes

[a]The WINDOW PANE subset is designated by the beginning date measured either by days before (DBT) or after transplanting (DAT) and duration (time) measured by days from beginning date.
[b]Descriptions of meteorological factors are presented in Table II.2.
[c]Correlation coefficients (r) are significant with $P \leq 0.001$. When an "a" follows the r, $P \leq 0.01$; a "b" means that $P \leq 0.05$.

Table II.4b. Meteorological factors highly correlated with rice blast on IR50 and C22 cultivars at Cavinti, Laguna, Philippines as found by WINDOW PANE program.[a]

	Cultivars					
	IR50			C22		
Meteorological factor[b]	Beginning date	Time (days)	Correlation coefficient[c]	Beginning date	Time (days)	Correlation coefficient
Percent maximum diseased leaf area						
MMAX	30DAS	4	0.72a	20DAS	14	0.67a
DG25C	20DBS	54	0.68a			
MMIN	10DAS	23	0.79	20DAS	11	0.72a
	20DAS	11	0.80	10DAS	5	0.70a
	20DAS	9	0.80			
PFREQ	10DBS	5	-0.73	30DAS	3	-0.58b
TPREC	30DAS	3	0.71a	20DBS	38	0.62b
				10DAS	6	0.77
CDWP	10DBS	5	-0.78			
MAVE	10DAS	23	0.74	20DAS	13	0.69a
	10DAS	21	0.72a			
PDD	10DAS	23	0.74	20DAS	13	0.69a
	10DAS	21	0.72a			
DOPT	0DBS	29	-0.64a	20DAS	6	-0.73a
CDOPT	10DBS	6	-0.71a			
MWS	20DBS	56	-0.77			
	20DAS	16	-0.80			
	20DAS	9	-0.80			
MSR				10DBS	45	0.70a
				20DAS	21	0.73a
				20DAS	10	0.76a

Table II.4b. (continued)

Meteorological factor	IR50 Beginning date	IR50 Time (days)	IR50 Correlation coefficient	C22 Beginning date	C22 Time (days)	C22 Correlation coefficient
	Cultivars					
	IR50			C22		
Meteorological factor	Beginning date	Time (days)	Correlation coefficient	Beginning date	Time (days)	Correlation coefficient
Percent maximum diseased leaf area						
DR84	20DBS	47	0.65a	30DBS	57	0.75a
				0DBS	27	0.73a
DWS35	30DBS	66	-0.74	10DBS	46	-0.78
	20DBS	56	-0.75			
Percent final diseased leaf area						
MMAX	20DBS	53	0.56b	30DBS	70	-0.58b
DG25C	20DBS	54	0.54b	10DAS	6	-0.75a
MMIN	20DAS	6	0.76			
TPREC	30DBS	47	0.70a			
CDWP				30DBS	48	0.71a
				20DBS	37	0.77
				10DAS	7	0.64a
MAVE				30DBS	70	-0.57b
DOPT	20DAS	6	-0.57b			
DRH80	10DBS	32	0.52b			
	0DBS	22	0.57b			
MRH	30DAS	6	0.55b			
MWS	30DBS	65	-0.73	10DAS	9	0.75a
	20DBS	55	-0.74	30DAS	11	0.73a
MSR				20DBS	38	-0.69a
				10DAS	8	-0.68a
DR84	30DBS	57	0.71a			
DWS35	10DBS	46	-0.68a	0DBS	38	0.75a
				10DAS	30	0.75a

Table II.4b. (continued)

	Cultivars					
	IR50			C22		
Meteorological factor	Beginning date	Time (days)	Correlation coefficient	Beginning date	Time (days)	Correlation coefficient
Percent panicle blast severity						
MMAX				30DAS	27	-0.59b
				40DAS	4	-0.73a
DG25C				50DAS	9	0.85
MMIN				50DAS	26	-0.57b
PFREQ	10DAS	54	-0.58b			
	50DAS	14	-0.60b			
TPREC	30DBS	67	-0.52b	20DAS	65	-0.83
				50DAS	26	-0.81
				50DAS	24	-0.83
CDWP	40DAS	39	-0.56b			
	50DAS	12	-0.61b			
CDWOP	10DAS	37	0.59b			
	30DAS	17	0.58b			
DOPT	50DAS	22	-0.58b	30DAS	34	-0.75a
CDOPT				30DAS	34	-0.82
				40DAS	26	-0.72a
MRH	20DAS	29	-0.58b			
MWS				40DAS	8	0.72a
MSR	50DAS	6	0.58b			
DR84				0DBS	52	-0.69a
DWS35				20DAS	34	0.63b

Table II.4b. Footnotes

[a]The WINDOW PANE subset is designated by the beginning date measured either by days before (DBS) or after (DAS) sowing, and duration (time) measured by days from beginning date.
[b]Descriptions of meteorological factors are presented in Table II.2.
[c]Correlation coefficients (r) are significant with $P \leq 0.001$. When an "a" follows r, $P \leq 0.01$; a "b" means that $P \leq 0.05$.

Table II.4c. Meteorological factors highly correlated with rice blast on IR50 cultivar at the IRRI blast nursery, Philippines as found by WINDOW PANE program.[a]

Meteorological factor[b]	Beginning date	Time (days)	Correlation coefficient[c]
Percent final diseased leaf area			
DG25C	30DBS	67	0.58
	20DBS	57	0.58
	10DBS	48	0.55
	20DAS	13	0.41b
	20DAS	10	0.41b
PFREQ	20DAS	4	0.53
CDWP	20DBS	44	0.41b
CDWOP	30DBS	55	-0.50a
	10DBS	35	-0.47a
	20DAS	6	-0.51a
MWS	20DAS	7	-0.41b
Percent panicle blast severity			
DG25C	20DBS	70	0.52a
	20DBS	54	0.48a
	20DBS	52	0.48a
DRH80	20DBS	89	0.46a
CDRH80	20DBS	89	0.50a
MRH	20DBS	94	0.40b

[a]The WINDOW PANE subset is designated by the beginning date measured either by days before (DBS) or after sowing (DAS) and duration (time) measured by days from beginning date.
[b]Descriptions of meteorological factors are presented in Table II.2.
[c]Correlation coefficients (r) are significant with P≤ 0.001. When an "a" follows the r, P≤ 0.01; a "b" means that P≤ 0.05.

Table II.4d. Meteorological factors highly correlated with panicle blast index on C22 cultivar at Gunung Medan, West Sumatra, Indonesia as found by WINDOW PANE program.[a]

Meteorological factor[b]	Beginning date	Time (days)	Correlation coefficient[c]
MMAX	41DAS	10	0.82a
MMIN	19DBS	44	-0.67b
	21DAS	44	0.66b
PFREQ	1DAS	62	0.90
	11DAS	59	0.93
CDWP	1DAS	62	0.91
	1DAS	60	0.93
	11DAS	58	0.92
CDWOP	1DAS	69	-0.82a
	11DAS	59	-0.83a
MAVE	41DAS	12	0.74b
DOPT	29DBS	64	0.70b
	19DBS	53	0.73b
CDOPT	19DBS	52	0.74b
	19DBS	47	0.73b
DRH80	9DBS	45	0.77a
	11DAS	11	0.81a
CDRH80	9DBS	44	0.75b
	11DAS	10	0.79a
MRH	1DAS	34	0.71b
MSR	19DBS	49	-0.73b

[a]The WINDOW PANE subset is designated by the beginning date measured either by days before (DBS) or after sowing (DAS) and duration (time) measured by days from beginning date.
[b]Descriptions of meteorological factors are presented in Table II.2.
[c]Correlation coefficients (r) are significant with P≤ 0.001. When an "a" follows the r, P≤ 0.01; a "b" means that P≤ 0.05.

Table II.4e. Meteorological factors highly correlated with disease parameters of rice blast on C22 cultivar at Sitiung, West Sumatra, Indonesia as found by WINDOW PANE program.[a]

Meteorological factor[b]	Beginning date	Time (days)	Correlation coefficient[c]
Final leaf blast index			
TPREC	10DAS	10	-0.65b
CDWP	30DBS	47	-0.60b
	0DBS	14	-0.62b
DOPT	10DAS	31	-0.68b
CDOPT	10DAS	30	-0.68b
MSR	30DBS	51	0.63b
	10DBS	32	0.62b
	10DBS	27	0.63b
	0DBS	23	0.67b
Panicle blast index			
MMAX	0DBS	21	-0.78a
	0DBS	19	-0.81a
DG25C	10DBS	40	-0.78a
	0DBS	38	-0.77a
	0DBS	30	-0.80a
MMIN	0DBS	19	-0.65b
PFREQ	10DAS	10	-0.71b
TPREC	10DBS	78	-0.73b
CDWP	0DBS	31	-0.70b
CDWOP	10DAS	24	0.68b
MAVE	0DBS	21	-0.73b
	0DBS	19	-0.76b
DOPT	0DBS	41	-0.77a
	10DBS	40	-0.72b
CDOPT	0DBS	41	-0.76b
	0DBS	40	-0.76b
DRH80	10DBS	30	0.66b

[a]The WINDOW PANE subset is designated by the beginning date measured either by days before (DBS) or after sowing (DAS) and duration (time) measured by days from beginning date.
[b]Descriptions of meteorological factors are presented in Table II.2.
[c]Correlation coefficients (r) are significant with P≤ 0.001. When an "a" follows the r, P≤ 0.01; a "b" means that P≤ 0.05.

Table II.5a. Models for predicting disease parameters (Y) of rice blast on Jin heung cultivar under two nitrogen treatments at Icheon, South Korea. Model is presented in the form, $Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n$.

Dependent variable (Y)	Predictors				Statistic[a]				ACC[b]
	n=0	n=1	n=2	n=3	1	2	3	4	(%)
Y = ML1[c]									
$Y^{1/2}$-I									
X_n[d]		ln(MSD 7A21)	CDRH80 $17B45^{1/6}$	MSD $1B41^{4}$	0.82	4520.38	17.81	0.40	69
β_n[e]	56.093^{**}	-25.706^{**}	$+3.700^{**}$	$4.940\times10^{-4*}$					
VIF_n[f]	0.000	3.598	1.004	3.595					
$Y^{1/3}$-II									
X_n		TPREC 7A19	DRH80 $5B34^{1/6}$	-	0.70	23693.01	15.53	0.60	75
β_n	-3.471^{ns}	$+0.009^{**}$	$+4.554^{**}$						
VIF_n	0.000	1.036	1.036						
$Y^{1/3}$-III									
X_n		TPREC 7A19	DRH80 $5B34^{1/6}$	-	0.97	15527.10	17.70	0.72	81
β_n	-	$+0.009^{**}$	$+2.092^{**}$						
VIF_n	-	2.627	2.627						
$Y^{1/4}$-IV									
X_n		TPREC $7A23^{1/2}$	DRH80 $5B34^{1/6}$	-	0.70	26835.26	11.88	0.69	75
β_n	-1.373^{ns}	$+0.078^{**}$	$+2.348^{**}$						
VIF_n	0.000	1.075	1.075						
ln(Y)-V									
X_n		TPREC $7A23^{1/4}$	DRH80 7A22	DRH80 $5B34^{1/6}$	0.82	11630.99	11.34	0.93	88
β_n	-10.183^{**}	$+0.948^{**}$	-0.157^{*}	$+8.666^{**}$					
VIF_n	0.000	1.341	5.227	4.529					

Table II.5a. (continued)

Dependent variable (Y)	Predictors				Statistic				ACC (%)
	n=0	n=1	n=2	n=3	1	2	3	4	
Y = ML2									
Y-I									
X_n		DRH80 3A2	CDRH80 3A2	-					
$ß_n$	114.811**	+67.539**	+177.930**	-	0.67	34296.80	30.45	0.57	75
VIF_n	0.000	1.161	1.161	-					
Y-II									
X_n		DRH80 3A2	CDRH80 3A2	DOPT 13B10$^{1/6}$					
$ß_n$	133.757**	+53.922*	+172.660*	-21.314**	0.70	33155.51	28.80	0.34	75
VIF_n	0.000	1.300	1.167	1.163					
$Y^{1/2}$-III									
X_n		ln(CDRH80 3A2+.01)	DOPT 13B10$^{1/2}$	-					
$ß_n$	18.982**	+0.556*	-2.148*	-	0.54	36180.05	17.72	0.50	69
VIF_n	0.000	1.055	1.055	-					
$Y^{1/2}$-IV									
X_n		ln(CDRH80 3A2+.01)	DOPT 13B10$^{1/6}$	DRH80 3A2					
$ß_n$	16.812**	+0.450*	-1.636**	+2.169*	0.61	2855.17	16.22	0.96	75
VIF_n	0.000	1.174	1.176	1.293					
$Y^{1/3}$-V									
X_n		ln(CDRH80 3A2+.01)	DOPT 13B10$^{1/2}$	DRH80 3A2					
$ß_n$	6.484**	+0.118*	-0.508*	+0.632*	0.58	29601.71	11.38	0.99	81
VIF_n	0.000	1.174	1.176	1.293					

Table II.5a. (continued)

Dependent variable (Y)	Predictors				Statistic[a]				ACC (%)
	n=0	n=1	n=2	n=3	1	2	3	4	
Y = FL1									
Y-I									
X_n		DRH80 $7A21^{1/2}$	TPREC $1B41^{3}$	-					
$ß_n$	-11.665^{*}	$+8.135^{**}$	$+6.920\text{x}10^{-7**}$	-	0.89	982.93	36.51	0.95	81
VIF_n	0.000	1.580	1.580	-					
$Y^{1/2}$-II									
X_n		DRH80 $5B40^{1/6}$	TPREC $1B41^{3}$	-					
$ß_n$	-4.415^{*}	$+4.795^{**}$	$+7.785\text{x}10^{-8**}$	-	0.89	1097.10	18.20	0.68	88
VIF_n	0.000	1.607	1.607	-					
$Y^{1/3}$-III									
X_n		DRH80 $5B40^{1/6}$	TPREC $1B41^{3}$	-					
$ß_n$	-1.373^{ns}	$+2.223^{**}$	$+3.128\text{x}10^{-8**}$	-	0.86	1097.19	13.99	0.26	88
VIF_n	0.000	1.607	1.607	-					
$Y^{1/5}$-IV									
X_n		DRH80 $5B40^{1/6}$	TPREC $1B41^{3}$	-					
$ß_n$	-	$+0.992^{**}$	$+1.275\text{x}10^{-8**}$	-	0.99	1098.54	9.70	0.10	88
VIF_n	-	1.889	1.889	-					
$Y^{1/6}$-V									
X_n		DRH80 $5B40^{1/6}$	TPREC $1B41^{3}$	-					
$ß_n$	-	$+0.940^{*}$	$+8.706\text{x}10^{-9**}$	-	0.99	1117.95	8.59	0.28	88
VIF_n	-	1.889	1.889	-					

Table II.5a. (continued)

Dependent variable (Y)	Predictors				Statistic				ACC (%)
	n=0	n=1	n=2	n=3	1	2	3	4	
Y = FL2									
Y-I									
X_n		ln(PFREQ 7A28)	DRH80 $3A20^{3}$	-					
$ß_n$	-57.519^{**}	$+27.092^{**}$	$+33.181^{**}$	-	0.83	1470.98	17.04	0.68	88
VIF_n	0.000	1.096	1.096	-					
$Y^{1/2}$-II									
X_n		CDRH80 $3A20^{1/2}$	DG25C $17B48^{4}$	CDWOP $7A23^{3}$					
$ß_n$	8.001^{**}	$+0.695^{**}$	$-6.170\text{x}10^{-7*}$	$-5.400\text{x}10^{-4**}$	0.92	887.47	6.71	0.84	88
VIF_n	0.000	1.039	1.039	1.368					
$Y^{1/3}$-III									
X_n		CDRH80 $3A20^{1/2}$	CDWOP $1B36^{4}$	-					
$ß_n$	3.841^{**}	$+0.254^{**}$	$+2.388\text{x}10^{-6**}$	-	0.93	931.60	4.46	0.40	75
VIF_n	0.000	1.016	1.016	-					
$Y^{1/4}$-IV									
X_n		CDRH80 $3A20^{1/2}$	CDWOP $1B36^{4}$	-					
$ß_n$	2.749^{**}	$+0.135^{**}$	$-1.343\text{x}10^{-6**}$	-	0.93	956.50	3.30	0.45	75
VIF_n	0.000	1.016	1.016	-					
$Y^{1/6}$-V									
X_n		CDRH80 $3A20^{1/3}$	DG25C $17B48^{4}$	CDWOP $7A23^{4}$					
$ß_n$	1.967^{**}	$+0.089^{**}$	$-5.109\text{x}10^{-8**}$	$-3.008\text{x}10^{-6**}$	0.94	810.44	2.11	0.83	88
VIF_n	0.000	1.022	1.332	1.355					

Table II.5a. (continued)

Dependent variable (Y)	Predictors				Statistic[a]				ACC (%)
	n=0	n=1	n=2	n=3	1	2	3	4	
Y = PBI1									
Y-I									
X_n		TPREC 3A20	-	-	0.82	3209.30	49.99	0.39	94
$ß_n$	-	+ 0.360**	-	-					
VIF_n	-	1.000	-	-					
Y = PBI2									
Y-I									
X_n		DRH80 $25B70^2$	-	-	0.61	5404.10	25.42	0.27	88
$ß_n$	94.840**	-0.043**	-	-					
VIF_n	0.000	1.000	-	-					
ln(Y)-II									
X_n		DRH80 $25B70^3$	-	-	0.74	4828.65	7.72	0.12	88
$ß_n$	4.508**	$-2.224 \times 10^{-5**}$	-	-					
VIF_n	0.000	1.000	-	-					
$Y^{1/4}$-III									
X_n		DRH80 $25B70^2$	-	-	0.70	5373.85	7.59	0.08	88
$ß_n$	3.169**	$-6.120 \times 10^{-4**}$	-	-					
VIF_n	0.000	1.000	-	-					
$Y^{1/5}$-IV									
X_n		DRH80 $25B70^2$	-	-	0.71	5442.58	6.15	0.08	88
$ß_n$	2.520**	$-4.060 \times 10^{-4**}$	-	-					
VIF_n	0.000	1.000	-	-					
$Y^{1/6}$-V									
X_n		DRH80 $25B70^2$	-	-	0.71	5494.59	5.17	0.09	88
$ß_n$	2.162**	$-2.990 \times 10^{-4**}$	-	-					
VIF_n	0.000	1.000	-	-					

Table II.5a. Footnotes

[a]1= Adjusted coefficient of determination (adjusted-R^2); 2= Allen's predicted error sum of squares (PRESS); 3= coefficient of variation (CV); 4= Shapiro and Wilk's probability less than W to test normality of studentized residuals.
[b]ACC= Accuracy expressed as percentage. Based on contingency quadrant (Fig. II.3) where ACC= (quadrant I + quadrant IV)/n, n is the number of observations where predictions were made.
[c]Disease parameters (DP) of rice blast. ML= Maximum lesion number; FL= final lesion number; PBI= percent panicle blast incidence. A "1" following DP would mean 110 kgN/ha treatment; "2" means 220 kgN/ha treatment.
[d]The convention used for predictor variables (X) indicates weather factors with beginning date expressed as days after (A) or before (B) transplanting, and duration in days; e.g. ln(MSD 7A21) is the average sunshine duration in hours expressed in natural logarithm (ln) starting 7 days after transplanting with 21 days duration. Descriptions of meteorological factors are presented in Table II.2.
[e]Regression coefficients ($ß_n$) followed by two asterisks (**) mean that $P \leq 0.001$; one asterisk (*) means $P \leq 0.05$; ns means $P > 0.05$.
[f]VIF= Variance inflation factor.

Table II.5b. Models for predicting disease parameters (Y) of rice blast on Jin heung cultivar at Icheon, South Korea under combined data sets of two nitrogen treatments. Model is represented in the form, $Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n$.

Dependent variable (Y)	Predictors n=0	n=1	n=2	n=3	Statistic[a] 1	2	3	4	ACC[b] (%)
Y = ML[c]									
$Y^{1/2}$-I									
X_n^{d}		N	DRH80 1B30^3	-	0.59	100116.10	26.22	0.37	88
β_n^{e}	-7.060^{*}	$+27.092^{**}$	$+5.470^{**}$	-					
VIF_n^{f}	0.000	1.004	1.004	-					
$Y^{1/3}$-II									
X_n		N	ln(DRH80 9B41)	-	0.59	102099.60	18.30	0.48	88
β_n	0.362^{ns}	$+0.015^{**}$	$+0.724^{**}$	-					
VIF_n	0.000	1.002	1.002	-					
$Y^{1/4}$-III									
X_n		N	ln(DRH80 9B41)	-	0.59	104074.80	14.22	0.65	88
β_n	0.880^{*}	$+0.008^{**}$	$+0.389^{**}$	-					
VIF_n	0.000	1.002	1.002	-					
$Y^{1/5}$-IV									
X_n		N	ln(DRH80 9B41)	-	0.58	105841.90	11.68	0.71	88
β_n	1.019^{**}	$+0.005^{**}$	$+0.256^{**}$	-					
VIF_n	0.000	1,002	1.002	-					
$Y^{1/6}$-V									
X_n		N	ln(DRH80 9B41)	-	0.58	107369.00	9.93	0.70	88
β_n	1.066^{**}	$+0.004^{**}$	$+0.187^{**}$	-					
VIF_n	0.000	1.002	1.002	-					

Table II.5b. (continued)

Dependent variable (Y)	Predictors				Statistic				ACC (%)
	n=0	n=1	n=2	n=3	1	2	3	4	
Y = FL									
$Y^{1/2}$-I									
X_n		DRH80 5B34	N	CDWP $7A24^{1/2}$					
$ß_n$	-2.407^{**}	$+0.181^{**}$	$+0.033^{**}$	$+0.503^{*}$	0.77	6758.88	23.43	0.24	88
VIF_n	0.000	1.181	1.006	1.178					
$Y^{1/3}$-II									
X_n		DRH80 $5B34^{1/3}$	N	CDWP 7A24					
$ß_n$	-1.372^{*}	$+1.006^{**}$	$+0.013^{**}$	$+0.067^{*}$	0.76	9066.09	17.03	0.27	88
VIF_n	0.000	1.138	1.005	1.133					
$Y^{1/4}$-III									
X_n		DRH80 $5B34^{1/6}$	N	CDWP 7A24					
$ß_n$	-1.530^{*}	$+1.714^{**}$	$+0.008^{**}$	$+0.039^{*}$	0.75	5978.99	13.62	0.63	84
VIF_n	0.000	1.123	1.005	1.118					
$Y^{1/5}$-IV									
X_n		DRH80 $5B34^{1/6}$	N	CDWP 7A24					
$ß_n$	0.717^{ns}	$+1.192^{**}$	$+0.005^{**}$	$+0.027^{*}$	0.74	15332.60	11.46	0.80	88
VIF_n	0.000	1.123	1.005	1.118					
$Y^{1/6}$-V									
X_n		DRH80 $5B34^{1/6}$	N	CDWP 7A24					
$ß_n$	-0.284^{ns}	$+0.907^{**}$	$+0.004^{**}$	$+0.020^{*}$	0.73	34039.21	9.90	0.80	88
VIF_n	0.000	1.123	1.005	1.118					

Table II.5b. (continued)

Dependent variable (Y)	Predictors				Statistic				ACC (%)
	n=0	n=1	n=2	n=3	1	2	3	4	
Y = PBI									
$Y^{1/2}$-I									
X_n		DR84 25B63	N	CDRH80 $9B51^{4}$	0.77	6924.51	18.06	0.65	81
$ß_n$	2.824^{**}	-2.639^{**}	$+0.028^{**}$	$-3.101x10^{-6**}$					
VIF_n	0.000	1.013	1.004	1.010					
$Y^{1/3}$-II									
X_n		DR84 25B63	N	CDRH80 $9B51^{4}$	0.79	6581.43	12.03	0.86	84
$ß_n$	2.116^{**}	-0.955^{**}	$+0.010^{**}$	$-1.225x10^{-6**}$					
VIF_n	0.000	1.013	1.004	1.010					
$Y^{1/4}$-III									
X_n		DR84 25B63	N	CDRH80 $9B51^{4}$	0.80	6478.19	9.03	0.83	84
$ß_n$	1.781^{**}	-0.529^{**}	$+0.006^{**}$	$-7.130x10^{-7**}$					
VIF_n	0.000	1.013	1.004	1.010					
$Y^{1/5}$-IV									
X_n		DR84 25B63	N	CDRH80 $9B51^{4}$	0.80	6433.00	7.24	0.83	84
$ß_n$	1.596^{**}	-0.353^{**}	$+0.004^{**}$	$-4.910x10^{-7**}$					
VIF_n	0.000	1.013	1.004	1.010					
$Y^{1/6}$-V									
X_n		DR84 25B63	N	CDRH80 $9B51^{4}$	0.81	6408.72	6.04	0.77	84
$ß_n$	1.481^{**}	-0.261^{**}	$+0.003^{**}$	$-3.710x10^{-7**}$					
VIF_n	0.000	1.013	1.004	1.010					

Table II.5b. Footnotes

[a]1= Adjusted coefficient of determination (adjusted-R^2); 2= Allen's predicted error sum of squares (PRESS); 3= coefficient of variation (CV); 4= Shapiro and Wilk's probability less than W to test normality of studentized residuals.

[b]ACC= Accuracy expressed as percentage. Based on contingency quadrant (Fig. II.3) where ACC= (quadrant I + quadrant IV)/n, n is the number of observations where predictions were made.

[c]Disease parameters (DP) of rice blast. ML= Maximum lesion number; FL= final lesion number; PBI= percent panicle blast incidence.

[d]The convention used for predictor variables (X) indicates weather factors with beginning date expressed as days after (A) or before (B) transplanting, and duration in days; e.g. DRH80 $5B34^{1/6}$ is the number of days with relative humidity ≥ 80% expressed in 6th root starting 5 days before transplanting with 34 days duration. N= Nitrogen amount in kgN/ha. Descriptions of meteorological factors are presented in Table II.2.

[e]Regression coefficients ($ß_n$) followed by two asterisks (**) mean that $P \leq 0.001$; one asterisk (*) means $P \leq 0.05$; ns means $P > 0.05$.

[f]VIF= Variance inflation factor.

Table II.5c. Models for predicting disease parameters (Y) of rice blast on IR50 cultivar at Cavinti, Laguna, Philippines. Model is presented in the form, $Y = \beta_0 + \beta_1 X_1 + ... + \beta_n X_n$.

Dependent variable (Y)	Predictors					Statistic[a]				ACC[b] (%)
	n=0	n=1	n=2	n=3	n=4	1	2	3	4	
Y = MDLA[c]										
Y-I										
X_n[d]		DWS35 20B56$^{1/3}$	-	-	-					
β_n[e]	97.649**	-7.482**	-	-	-	0.64	274.98	4.10	0.10	94
VIF_n[f]	0.000	1.000	-	-	-					
Y-II										
X_n		DWS35 20B56$^{1/3}$	$N^{1/6}$	-	-					
β_n	85.751**	-7.527**	+5.438^{ns}	-	-	0.65	285.50	4.06	0.24	94
VIF_n	0.000	1.001	1.001	-	-					
Y-III										
X_n		DWS35 20B56$^{1/3}$	$N^{1/3}$	N^4	-					
β_n	74.517**	-7.812*	+5.383^{ns}	-2.906×10^{-9}^{ns}	-	0.70	271.42	3.76	0.32	94
VIF_n	0.000	1.016	6.940	6.940	-					
Y-IV										
X_n		MMAX 10B16	CDWP 10B5	N	-					
β_n	129.080**	-0.792^{ns}	-5.185*	+0.016^{ns}	-	0.57	433.57	4.50	0.92	88
VIF_n	0.000	6.690	6.880	1.060	-					
$Y^{1/2}$-V										
X_n		MMAX 10B16	DWS35 20B56	$N^{1/6}$	-					
β_n	9.849**	-0.021^{ns}	-0.459*	+0.313^{ns}	-	0.61	328.78	2.19	0.14	94
VIF_n	0.000	4.513	4.510	1.018	-					

Table II.5c. (continued)

Dependent variable (Y)	Predictors					Statistic				ACC (%)
	n=0	n=1	n=2	n=3	n=4	1	2	3	4	
Y = FDLA										
Y-I										
X_n		DWS35 10B46	TPREC 30B47	ln(N)	-					
$ß_n$	78.083**	-6.852*	+0.015*	+2.086^{ns}	-	0.62	338.82	4.48	0.07	94
VIF_n	0.000	1.346	1.326	1.057	-					
Y-II										
X_n		DWS35 10B46	DRH80 0B22	ln(N)	-					
$ß_n$	40.607*	-9.768**	+1.626*	+2.249^{ns}	-	0.68	302.04	4.14	0.01	94
VIF_n	0.000	1.023	1.018	1.040	-					
Y-III										
X_n		DWS35 10B46	MRH 30A6	ln(N)	-					
$ß_n$	-35.113^{ns}	-8.804*	+1.333*	+2.041^{ns}	-	0.69	272.99	4.09	0.05	94
VIF_n	0.000	1.047	1.044	1.051	-					
Y-IV										
X_n		DWS35 10B46	MRH 30A6	N	-					
$ß_n$	-	-8.955**	+1.032**	+0.013^{ns}	-	0.99	272.00	4.09	0.06	94
VIF_n	-	1.698	4.427	4.231	-					
Y-V										
X_n		DWS35 10B46	DRH80 10B32	N	-					
$ß_n$	-	-8.476**	+2.969**	+0.014^{ns}	-	0.99	340.78	4.44	0.00	94
VIF_n	-	1.694	4.407	4.407	-					

Table II.5c. (continued)

Dependent variable (Y)	Predictors					Statistic				ACC
	n=0	n=1	n=2	n=3	n=4	1	2	3	4	(%)
Y = PBS										
Y-I										
X_n		PFREQ 10A54	N^4	-	-					
$ß_n$	104.804^{**}	-0.935^{**}	-1.101×10^{-9ns}	-	-	0.76	419.90	8.04	0.47	73
VIF_n	0.000	1.071	1.071							
Y-II										
X_n		PFREQ 10A54	CDWOP 10A17	-	-					
$ß_n$	199.812^{**}	-3.097^{**}	-6.160^{*}	-	-	0.87	255.41	6.01	0.48	80
VIF_n	0.000	36.550	36.550	-	-					
$Y^{1/2}$-III										
X_n		PFREQ 10A54	N^4	-	-					
$ß_n$	10.328^{**}	-0.053^{**}	6.560×10^{-11ns}	-	-	0.74	423.27	4.12	0.42	73
VIF_n	0.000	1.071	1.071	-	-					
$Y^{1/5}$-IV										
X_n		PFREQ $10A54^2$	N^4	-	-					
$ß_n$	2.486^{**}	$-1.000 \times 10^{-4**}$	$-7.216 \times 10^{-12*}$	-	-	0.72	285.60	1.67	0.23	80
VIF_n	0.000	1.072	1.072	-	-					
$Y^{1/5}$-V										
X_n		CDWP 40A39	PREQ $10A54^2$	-	-					
$ß_n$	2.406^{**}	$+0.015^{*}$	$-3.000 \times 10^{-4**}$	-	-	0.82	428.13	1.32	0.49	80
VIF_n	0.000	16.240	16.240							

Table II.5c. Footnotes

[a]1= Adjusted coefficient of determination (adjusted-R^2); 2= Allen's predicted error sum of squares (PRESS); 3= coefficient of variation (CV); 4= Shapiro and Wilk's probability less than W to test normality of studentized residuals.
[b]ACC= Accuracy expressed as percentage. Based on contingency quadrant (Fig. II.3) where ACC= (quadrant I + quadrant IV)/n, n is the number of observations where predictions were made.
[c]Disease parameters (DP) of rice blast. MDLA= Percent maximum diseased leaf area; FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.
[d]The convention used for predictor variables (X) indicates weather factors with beginning date expressed as days after (A) or before (B) sowing, and duration in days; e.g. DWS35 $20B56^{1/3}$ is the number of days with wind speed ≥ 3.5 m/s expressed in cube root starting 20 days before sowing with 56 days duration. N= nitrogen amount in kgN/ha. Descriptions of meteorological factors are presented in Table II.2.
[e]Regression coefficients ($ß_n$) followed by two asterisks (**) mean that P ≤ 0.001; one asterisk (*) means P ≤ 0.05; ns means P > 0.05.
[f]VIF= Variance inflation factor.

Table II.5d. Models for predicting disease parameters (Y) of rice blast on C22 cultivar at Cavinti, Laguna, Philippines. Model is presented in the form, $Y = ß_0 + ß_1X_1 + ... + ß_nX_n$.

Dependent variable (Y)	Predictors					Statistic[a]				ACC[b] (%)
	n=0	n=1	n=2	n=3	n=4	1	2	3	4	
Y = MDLA[c]										
$Y^{1/2}$-I										
X_n[d]		ln(MMIN 10A5)	PFREQ 30A3^4	N^3	-	0.95	1578.95	13.70	0.09	87
$ß_n$[e]	-62.834**	+22.617^{-8**}	-0.068**	+5.448x10^{-8ns}	-					
VIF_n[f]	0.000	1.003	1.012	1.011	-					
$Y^{1/3}$-II										
X_n		ln(MMIN 10A5)	PFREQ 30A3^4	N^3	-	0.96	1115.17	10.08	0.54	87
$ß_n$	-23.376**	+8.773**	-0.034**	+1.570x10^{-8ns}	-					
VIF_n	0.000	1.003	1.012	1.011	-					
$Y^{1/4}$-III										
X_n		ln(MMIN 10A5)	PFREQ 30A3^4	N^3	-	0.96	1351.56	8.32	0.69	87
$ß_n$	-12.919**	+5.058**	-0.022**	+6.863x10^{-9ns}	-					
VIF_n	0.000	1.003	1.012	1.011	-					
$Y^{1/5}$-IV										
X_n		ln(MMIN 10A5)	PFREQ 30A3^4	N^3	-	0.96	920.60	7.17	0.62	87
$ß_n$	-8.478**	+3.467**	-0.017**	+3.606x10^{-9ns}	-					
VIF_n	0.000	1.003	1.012	1.011	-					
$Y^{1/6}$-V										
X_n		ln(MMIN 10A5)	PFREQ 30A3^4	N^3	-	0.96	1785.16	6.32	0.69	73
$ß_n$	-6.104**	+2.610**	-0.013**	+2.087x10^{-9ns}	-					
VIF_n	0.000	1.003	1.012	1.011	-					

Table II.5d. (continued)

Dependent variable (Y)	Predictors					Statistic				ACC (%)
	n=0	n=1	n=2	n=3	n=4	1	2	3	4	
Y = FDLA										
$Y^{1/2}$-I										
X_n		CDWP $10A7^3$	MSR $10A8^4$	$N^{1/2}$	-	0.86	445.75	49.92	0.15	87
$ß_n$	-	$+0.067^{**}$	$+6.510x10^{-6*}$	-0.053^{ns}	-					
VIF_n	-	3.330	4.670	8.195	-					
$Y^{1/3}$-II										
X_n		CDWP $20B37^{1/2}$	MSR $10A8^4$	-	-	0.84	280.04	30.22	0.50	93
$ß_n$	-10.102^{**}	$+2.304^{**}$	$+1.228x10^{-5**}$	-	-					
VIF_n	0.000	4.332	4.332	-	-					
$Y^{1/4}$-III										
X_n		CDWP 20B37	MSR $10A8^3$	N^4	-	0.83	399.10	28.18	0.16	93
$ß_n$	-5.054^{**}	$+0.234^{**}$	$+2.860x10^{-4**}$	$-2.660x10^{-11ns}$	-					
VIF_n	0.000	5.877	5.921	1.037						
$Y^{1/5}$-IV										
X_n		CDWP 20B37	MSR $10A8^3$	N^4	-	0.82	568.60	27.47	0.09	93
$ß_n$	-4.455^{**}	$+0.206^{**}$	$+2.590x10^{-4**}$	$-3.260x10^{-11ns}$	-					
VIF_n	0.000	5.877	5.921	1.037	-					
$Y^{1/6}$-V										
X_n		CDWP $20B37^{1/6}$	MSR $10A8^4$	N^4	-	0.85	601.19	24.60	0.31	93
$ß_n$	-20.325^{**}	$+12.471^{**}$	$+9.109x10^{-6**}$	$-3.303x10^{-11ns}$	-					
VIF_n	0.000	4.435	4.480	1.041	-					

Table II.5d. (continued)

Dependent variable (Y)	Predictors					Statistic				ACC (%)
	n=0	n=1	n=2	n=3	n=4	1	2	3	4	
Y = PBS										
$Y^{1/2}$-I										
X_n		MMAX 30A27^{4}	TPREC 50A24^{3}	-	-					
β_n	9.232^{**}	$-3.500\times10^{-6**}$	$-2.460\times10^{-7**}$	-	-	0.97	960.14	9.70	0.18	80
VIF_n	0.000	1.132	1.132	-	-					
$Y^{1/2}$-II										
X_n		MMAX 30A27^{4}	TPREC 50A24^{3}	$N^{1/2}$	-					
β_n	8.164^{**}	$-3.187\times10^{-6**}$	$-2.510\times10^{-7**}$	$+0.080^{ns}$	-	0.98	1160.70	8.56	0.89	87
VIF_n	0.000	1.187	1.170	1.062	-					
$Y^{1/3}$-III										
X_n		TPREC 50A26^{4}	CDOPT 30A34^{4}	-	-					
β_n	4.380^{**}	$-4.006\times10^{-10**}$	$-9.460\times10^{-7**}$	-	-	0.99	870.64	6.39	0.78	87
VIF_n	0.000	2.494	2.494	-	-					
$Y^{1/6}$-IV										
X_n		MMAX 30A27^{4}	TPREC 50A24^{4}	CDOPT 40A26$^{1/6}$	$N^{1/2}$					
β_n	-6.723^{**}	$-4.900\times10^{-7**}$	$-2.548\times10^{-10**}$	$+5.227^{**}$	$+0.008^{*}$	0.99	599.90	2.22	0.71	87
VIF_n	0.000	2.400	1.790	3.435	1.060					
$Y^{1/6}$-V										
X_n		TPREC 50A24^{4}	$N^{1/2}$	-	-					
β_n	1.819^{**}	$-2.485\times10^{-10**}$	$+0.010^{ns}$	-	-	0.99	730.69	4.42	0.51	93
VIF_n	0.000	1.013	1.013							

Table II.5d. Footnotes

[a]1= Adjusted coefficient of determination (adjusted-R^2); 2= Allen's predicted error sum of squares (PRESS); 3= coefficient of variation (CV); 4= Shapiro and Wilk's probability less than W to test normality of studentized residuals.

[b]ACC= Accuracy expressed as percentage. Based on contingency quadrants (Fig. II.3) where ACC= (quadrant I + quadrant IV)/n, n is the number of observations where predictions were made.

[c]Disease parameters (DP) of rice blast. MDLA= Percent maximum diseased leaf area; FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.

[d]The convention used for predictor variables (X) indicates weather factors with beginning date expressed as days after (A) or before (B) sowing, and duration in days; e.g. ln(MMIN 10A5) is the mean minimum temperature expressed in natural logarithm starting 10 days after sowing with 5 days duration. N= nitrogen amount in kgN/ha. Descriptions of meteorological factors are presented in Table II.2.

[e]Regression coefficients ($ß_n$) followed by two asterisks (**) mean that $P \leq 0.001$; one asterisk (*) means $P \leq 0.05$; ns means $P > 0.05$.

[f]VIF= Variance inflation factor.

Table II.5e. Models for predicting disease parameters (Y) of rice blast on IR50 cultivar at the IRRI blast nursery, Philippines. Model is presented in the form, $Y = ß_0 + ß_1X_1 + ... + ß_nX_n$.

Dependent variable (Y)	Predictors n=0	n=1	n=2	n=3	Statistic[a] 1	2	3	4	ACC[b] (%)
Y = FDLA[c]									
Y-I									
X_n[d]		DG25C 30B67$^{1/6}$	DG25C 20A10$^{1/6}$	MWS 20A7^{4}	0.51	14952.03	32.92	0.88	71
$ß_n$[e]	-12506.000**	+5438.800**	+1113.400^{ns}	-1.736**					
VIF_n[f]	0.000	1.332	1.263	1.070					
Y-II									
X_n		DG25C 30B67$^{1/6}$	DG25C 20A10$^{1/6}$	CDWOP 30B55^{2}	0.55	13818.80	31.40	0.39	74
$ß_n$	-11335.000**	+4884.800*	+1072.560^{ns}	-0.024**					
VIF_n	0.000	1.375	1.254	1.109					
Y-III									
X_n		DG25C 30B67$^{1/6}$	DG25C 20A13$^{1/6}$	CDWOP 30B55^{2}	0.55	13818.80	31.40	0.39	74
$ß_n$	-11828.000**	+4884.806*	+1348.574^{ns}	-0.024**					
VIF_n	0.000	1.375	1.254	1.109					
Y-IV									
X_n		DG25C 20B57$^{1/6}$	CDWOP 10B35^{2}	-	0.52	14514.90	32.62	0.38	77
$ß_n$	-11210.000**	+5757.219**	-0.049**	-					
VIF_n	0.000	1.072	1.072	-					
$Y^{1/2}$-V									
X_n		DG25C 30B67$^{1/6}$	DG25C 20A10$^{1/6}$	CDWOP 30B55^{2}	0.52	15133.11	21.37	0.04	74
$ß_n$	-839.362**	+357.406*	+87.428^{ns}	-0.002**					
VIF_n	0.000	1.375	1.254	1.109					

Table II.5e. (continued)

Dependent variable (Y)	Predictors				Statistic				ACC (%)
	n=0	n=1	n=2	n=3	1	2	3	4	
Y = PBS									
$Y^{1/3}$-I									
X_n		DG25C $20B54^{1/6}$	MRH $20B94^{4}$	-	0.28	7744.46	7.59	0.65	62
$ß_n$	-120.821^{*}	$+63.804^{*}$	$+2.586\times10^{-8\,\mathrm{ns}}$	-					
VIF_n	0.000	1.014	1.014	-					
$Y^{1/4}$-II									
X_n		DG25C $20B54^{1/6}$	MRH $20B94^{4}$	-	0.28	7796.93	5.82	0.54	62
$ß_n$	-64.297^{*}	$+34.313^{*}$	$+1.374\times10^{-8\,\mathrm{ns}}$	-					
VIF_n	0.000	1.014	1.014	-					
$Y^{1/5}$-III									
X_n		DG25C $20B54^{1/6}$	MRH $20B94^{4}$	-	0.28	7830.78	4.72	0.47	62
$ß_n$	-41.700^{*}	$+22.491^{*}$	$+8.940\times10^{-9\,\mathrm{ns}}$	-					
VIF_n	0.000	1.014	1.014	-					
$Y^{1/6}$-IV									
X_n		DG25C $20B54^{1/6}$	MRH $20B94^{4}$	-	0.28	7854.21	3.97	0.43	62
$ß_n$	-30.106^{*}	$+16.413^{*}$	$+6.493\times10^{-9\,\mathrm{ns}}$	-					
VIF_n	0.000	1.014	1.014	-					
ln(Y)-V									
X_n		DG25C $20B54^{1/6}$	MRH $20B94^{4}$	-	0.29	7983.75	5.77	0.23	62
$ß_n$	-95.177^{*}	$+50.783^{*}$	$+1.961\times10^{-8\,\mathrm{ns}}$	-					
VIF_n	0.000	1.014	1.014	-					

Table II.5e. Footnotes

[a]1= Adjusted coefficient of determination (adjusted-R^2); 2= Allen's predicted error sum of squares (PRESS); 3= coefficient of variation (CV); 4= Shapiro and Wilk's probability less than W to test normality of studentized residuals.
[b]ACC= Accuracy expressed as percentage. Based on contingency quadrant (Fig. II.3) where ACC= (quadrant I + quadrant IV)/n, n is the number of observations where predictions were made.
[c]Disease parameters (DP) of rice blast. FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.
[d]The convention used for predictor variables (X) indicates weather factors with beginning date expressed as days after (A) or before (B) sowing, and duration in days; e.g. DG25C $30B67^{1/6}$ is the number of days with maximum temperature greater than 25 C expressed in 6th root starting 30 days before sowing with 67 days duration. Descriptions of meteorological factors are presented in Table II.2.
[e]Regression coefficients ($ß_n$) followed by two asterisks (**) mean that $P \leq 0.001$; one asterisk (*) means $P \leq 0.05$; ns means $P > 0.05$.
[f]VIF= Variance inflation factor.

Table II.5f. Models for predicting panicle blast index (Y) on C22 cultivar at Gunung Medan, West Sumatra, Indonesia. Model is presented in the form $Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n$.

Dependent variable (Y)	Predictors		Statistic[a]				ACC[b]
	n=0	n=1	1	2	3	4	(%)
Y = PBIn[c]							
Y-I							
X_n[d]		PFREQ 1A62^4	0.81	4.69	12.60	0.11	80
β_n[e]	2.002**	+3.000x10^{-6}**					
VIF_n[f]	0.000	1.000					
Y-II							
X_n		PFREQ 11A59$^{1/2}$	0.84	5.21	11.66	0.34	80
β_n	-14.912**	+3.651**					
VIF_n	0.000	1.000					
Y-III							
X_n		CDWP 1A62^3	0.88	3.12	10.06	0.18	90
β_n	2.452**	+2.000x10^{-4}**					
VIF_n	0.000	1.000					
Y-IV							
X_n		CDWP 1A60^3	0.90	2.76	9.46	0.28	80
β_n	2.526**	+2.000x10^{-4}**					
VIF_n	0.000	1.000					
Y-V							
X_n		CDWP 11A58$^{1/3}$	0.82	6.47	12.26	0.18	80
β_n	-11.559**	+6.100**					
VIF_n	0.000	1.000					

[a]1= Adjusted coefficient of determination (adjusted-R^2); 2= Allen's predicted error sum of squares (PRESS); 3= coefficient of variation (CV); 4= Shapiro and Wilk's probability less than W to test normality of studentized residuals.
[b]ACC= Accuracy expressed as percentage. Based on contingency quadrant (Fig. II.3) where ACC= (quadrant I + quadrant IV)/n, n is the number of observations where predictions were made.
[c]PBIn= Panicle blast index.
[d]The convention used for predictor variables (X) indicates weather factors with beginning date expressed as days after (A) or before (B) sowing, and duration in days; e.g. PFREQ 1A62^4 is precipitation frequency in days expressed at the 4th power starting 1 day after sowing with 62 days duration. Descriptions of meteorological factors are presented in Table II.2.
[e]Regression coefficients (β_n) followed by two asterisks (**) mean that $P \leq 0.001$; one asterisk (*) means $P \leq 0.05$; ns means $P > 0.05$.
[f]VIF= Variance inflation factor.

Table II.5g. Models for disease parameters (Y) of rice blast on C22 cultivar at Sitiung, West Sumatra, Indonesia. Model is presented in the form $Y = ß_0 + ß_1X_1 + \ldots + ß_nX_n$.

Dependent variable (Y)	Predictors n=0	Predictors n=1	Statistic[a] 1	Statistic[a] 2	Statistic[a] 3	Statistic[a] 4	ACC[b] (%)
Y = FLBIn[c]							
Y-I							
X_n[d]		TPREC 10A10$^{1/2}$	0.43	8.59	12.76	0.75	75
$ß_n$[e]	8.502**	-0.268*					
VIF_n[f]	0.000	1.000					
Y-II							
X_n		MSR 0B23^2	0.39	10.00	13.15	0.21	75
$ß_n$	4.777**	+0.014*					
VIF_n	0.000	1.000					
Y-III							
X_n		MSR 10B27^3	0.35	10.10	13.62	0.49	75
$ß_n$	5.350**	+8.000x10^{-4}*					
VIF_n	0.000	1.000					
Y-IV							
X_n		MSR 10B32$^{1/2}$	0.98	9.66	13.37	0.29	67
$ß_n$	-	+1.969**					
VIF_n	-	1.000					
Y-V							
X_n		ln(MSR 30B51)	0.98	9.44	13.15	0.72	75
$ß_n$	-	+2.727**					
VIF_n	-	1.000					
Y = PBIn							
Y-I							
X_n		ln(DG25C 0B30)	0.61	23.21	25.94	0.36	90
$ß_n$	78.947**	-21.916**					
VIF_n	0.000	1.000					
Y-II							
X_n		ln(DG25C 10B40)	0.56	25.20	27.38	0.11	90
$ß_n$	105.194**	-27.335**					
VIF_n	0.000	1.000					
Y-III							
X_n		ln(DG25C 0B38)	0.55	26.62	27.91	0.24	90
$ß_n$	105.263**	-27.740**					
VIF_n	0.000	1.000					
Y-IV							
X_n		DOPT 0B41^4	0.54	26.73	28.10	0.13	80
$ß_n$	16.087**	-4.000x10^{-6}**					
VIF_n	0.000	1.000					
Y-V							
X_n		CDOPT 0B40^4	0.53	27.98	28.30	0.16	80
$ß_n$	13.526**	-3.421x10^{-6}**					
VIF_n	0.000	1.000					

Table II.5g. Footnotes

[a]1= Adjusted coefficient of determination (adjusted-R^2); 2= Allen's predicted error sum of squares (PRESS); 3= coefficient of variation (CV); 4= Shapiro and Wilk's probability less than W to test normality of studentized residuals.
[b]ACC= Accuracy expressed as percentage. Based on contingency quadrants (Fig. II.3) where ACC= (quadrant I + quadrant IV)/n, n is the number of observations where predictions were made.
[c]FLBIn= Final leaf blast index; PBIn= panicle blast index.
[d]The convention used for predictor variables (X) indicates weather factors with beginning date expressed as days after (A) or before (B) sowing, and duration in days; e.g. TPREC $10A10^{1/2}$ is total precipitation in mm/day expressed in square root starting 10 days after sowing with 10 days duration. Descriptions of meteorological factors are presented in Table II.2.
[e]Regression coefficients ($ß_n$) followed by two asterisks (**) mean that $P \leq 0.001$; one asterisk (*) means $P \leq 0.05$; ns means $P > 0.05$.
[f]VIF= Variance inflation factor.

Table II.6a. Comparison of predicted and actual disease parameters (DP) of rice blast on Jin heung cultivar obtained in 1978 and 1983 as validation data using models generated for two nitrogen treatments at Icheon, South Korea.

Observation of disease (Year)	Actual DP (No. or %)	Predicted DP (No. or %)[a] Models I	II	III	IV	V
DP: ML1[b]						
1978	26.2	14.3	27.2	35.4	28.1	20.4
1983	71.4	0.3*	18.7*	28.1*	19.7*	17.8*
MDIFF[c]		41.5	25.8	17.0	24.9	29.7
LPE[d]		59.2	53.7	52.5	53.6	47.8
DP: ML2						
1978	34.4	114.8	27.2	60.5	63.6	63.4
1983	186.6	114.8*	91.1*	91.1*	86.9*	85.6*
MDIFF		-4.3	51.3	34.7	35.2	35.5
LPE		152.2	88.3	121.6	129.0	130.1
DP: FL1						
1978	8.2	39.4*	40.0*	34.5*	37.3*	33.3*
1983	20.3	2.0*	4.4*	4.3*	4.3*	3.9*
MDIFF		-6.5	-7.9	-7.2	-6.5	-4.4
LPE		49.5	47.7	46.2	45.1	41.5
DP: FL2						
1978	13.4	49.2	37.5	48.3	48.4*	76.3
1983	60.8	13.2*	9.9*	17.0*	17.2*	16.4*
MDIFF		5.9	13.4	4.5	4.3	-9.2
LPE		83.4	75.0	78.7	78.6	107.3
DP: PBI1						
1978	15.8	19.2	-	-	-	-
1983	22.4	6.0	-	-	-	-
MDIFF		6.5	-	-	-	-
LPE		19.8	-	-	-	-
DP: PBI2						
1978	42.1	75.9	73.8	70.6	70.2	69.9
1983	89.5	91.4	89.2	94.7	95.1	95.4
MDIFF		-17.8	-15.7	-16.9	-16.8	-16.8
LPE		31.9	32.0	23.4	22.5	22.0

Table II.6a. Footnotes

[a]Predicted DPs followed by an asterisk (*) are when prediction was severe but actual disease was light or vice-versa.
[b]ML= Maximum lesion number; FL= final lesion number; PBI= percent panicle blast incidence. A "1" following DP would mean 110 kgN/ha treatment; "2" means 220 kgN/ha treatment;
[c]MDIFF= Average of the difference of predicted value from actual value.
[d]LPE= length of prediction error computed as: MXPE - MNPE, where MXPE is the maximum prediction error (or maximum value obtained from calculating the difference of predicted from actual DP) and MNPE as the minimum prediction error (or minimum value obtained from calculating the difference of predicted from actual DP).

Table II.6b. Comparison of predicted and actual disease parameters (DP) of rice blast on Jin heung cultivar obtained in 1976, 1978, 1979, and 1988 as validation data using models generated when combining data set of two nitrogen treatments at Icheon, South Korea.

Observation of disease (Year)	Actual DP (No. or %)	Predicted DP (No. or %)[a] Models I	II	III	IV	V
DP: ML[b]						
1976	42.1	45.6	41.6	40.4	39.7	39.2
1978	34.4	135.0*	145.1*	143.1*	141.9*	141.1*
1979	132.8	144.0	137.2	134.7	133.2	132.0
1988	49.5	113.2*	107.3*	103.5*	101.0	99.3
MDIFF[c]		-45.6	-45.9	-43.6	-42.1	-41.0
LPE[d]		89.4	106.3	106.8	107.2	107.5
DP: FL						
1976	6.4	12.0	10.8	10.5	10.2	10.0
1978	13.4	46.5*	41.2*	40.0*	39.0*	38.4*
1979	68.0	50.7	47.8	47.2	46.5	46.1
1988	49.5	44.1	36.9	34.9*	33.9*	33.2*
MDIFF		-4.0	0.2	1.2	1.9	2.4
LPE		50.4	48.0	47.3	47.0	46.9
DP: PBI						
1976	27.1	33.5	32.2	31.6	31.2	31.0
1978	42.1	45.1	43.1	42.2	41.7	41.3
1979	97.4	78.8	79.2	79.5	79.8	80.0
1988	97.7	78.8	79.2	79.5	79.8	80.0
MDIFF		7.1	7.7	7.9	7.9	8.0
LPE		25.3	23.7	22.7	22.0	21.5

[a]Predicted DPs followed by an asterisk (*) are when prediction was severe but actual disease was light or vice-versa.
[b]ML= Maximum lesion number; FL= final lesion number; PBI= percent panicle blast incidence.
[c]MDIFF= Average of the difference of predicted value from actual value.
[d]LPE= length of prediction error computed as: MXPE - MNPE, where MXPE is the maximum prediction error (or maximum value obtained from calculating the difference of predicted from actual DP) and MNPE as the minimum prediction error (or minimum value obtained from calculating the difference of predicted from actual DP).

Table II.6c. Comparison of predicted and actual disease parameters (DP) of rice blast on IR50 and C22 cultivars for two randomly selected observations as validation data at Cavinti, Laguna, Philippines.

Observation of disease (DY/Year)[b]	IR50						C22					
	Actual DP (%)	Predicted DP (%)[a]					Actual DP (%)	Predicted DP (%)				
		Models						Models				
		I	II	III	IV	V		I	II	III	IV	V
DP: MDLA[c]												
165/1993	92.2	88.2	89.8	88.5	91.1	90.1	29.3	32.7	30.8	29.6	28.8	28.2
292/1993	96.8	97.6	97.8	100.0	96.0	97.9	32.1	42.6	37.4	33.8	31.4	29.7
MDIFF[d]		1.6	0.7	0.0	0.9	0.4		-7.0	-3.4	-1.0	-0.6	1.8
LPE[e]		4.8	3.4	7.4	0.3	0.4		7.2	3.8	1.5	0.2	1.3
DP: FDLA												
165/1993	88.6	91.0	90.3	89.8	91.2	89.4	2.9	1.1	3.0	2.3	2.0	1.5
292/1993	96.8	97.6	96.9	96.4	95.8	96.7	0.4	0.2	0.2	0.0	0.0	0.0
MDIFF		-1.7	-1.0	-0.4	-0.8	-0.4		1.0	0.1	0.5	0.7	0.9
LPE		1.6	1.6	1.6	3.6	0.9		1.5	0.4	0.2	0.5	0.9
DP: PBS												
165/1993	93.1	89.0	91.8	88.7	91.0	87.3	44.2	38.5	44.4	38.9	40.2	58.7
292/1993	86.1	64.7*	72.9*	64.5*	72.9*	65.1*	45.7	30.0*	34.8	29.7*	39.1	35.2
MDIFF		12.8	7.2	13.0	7.6	13.4		10.7	5.3	10.7	5.3	-2.0
LPE		17.3	12.0	17.2	11.2	15.3		10.0	11.2	10.7	2.7	25.0

Table II.6c. Footnotes

[a]Predicted DPs followed by an asterisk (*) are when prediction was severe but actual disease was light or vice-versa.
[b]DY= day of year, where January 1= DY 1 and December 31= DY 365 or 366 for non-leap and leap years, respectively.
[c]MDLA= Percent maximum diseased leaf area; FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.
[d]MDIFF= Average of the difference of predicted value from actual value or average prediction error.
[e]LPE= length of prediction error computed as: MXPE - MNPE, where MXPE is the maximum prediction error (or maximum value obtained from calculating the difference of predicted from actual DP) and MNPE as the minimum prediction error (or minimum value obtained from calculating the difference of predicted from actual DP).

Table II.6d. Comparison of predicted and actual disease parameters (DP) of rice blast on IR50 cultivar for five randomly selected observations as validation data at the IRRI blast nursery, Philippines.

Observation of disease (DY/Year)[b]	Actual DP (%)	Predicted DP (%)[a] Models I	II	III	IV	V
DP: FDLA[c]						
135/1990	76.2	72.6	59.8*	59.8*	64.5	53.3*
40/1991	71.8	86.8	83.0	83.0	83.2	83.9
80/1991	28.2	79.7*	81.2*	81.2*	81.5*	81.4*
211/1991	59.0	71.4*	48.0	48.0	58.2	40.4
119/1992	61.4	76.7*	72.6*	72.6*	68.2*	69.4*
MDIFF[d]		-18.2	-9.6	-9.6	-11.8	-6.4
LPE[e]		55.1	69.4	69.4	65.1	76.1
DP: PBS						
135/1990	100.0	90.8	90.9	91.0	91.1	91.6
1/1991	82.0	79.6	79.5	79.4	79.4	79.1
107/1991	53.3	83.8*	83.7*	83.7*	83.7*	83.7*
316/1991	73.1	90.4*	90.6*	90.7*	90.8*	91.2*
161/1992	45.3	54.3	53.9	53.7	53.5	52.7
MDIFF		-9.0	-9.0	-9.0	-9.0	-8.9
LPE		39.7	39.5	39.4	39.3	38.8

[a]Predicted DPs followed by an asterisk (*) are when prediction was severe but actual disease was light or vice-versa.
[b]DY= day of year, where January 1= DY 1 and December 31= DY 365 or 366 for non-leap and leap years, respectively.
[c]FDLA= percent final diseased leaf area; PBS= percent panicle blast severity;
[d]MDIFF= Average of the difference of predicted value from actual value or average prediction error.
[e]LPE= length of prediction error computed as: MXPE - MNPE, where MXPE is the maximum prediction error (or maximum value obtained from calculating the difference of predicted from actual DP) and MNPE as the minimum prediction error (or minimum value obtained from calculating the difference of predicted from actual DP).

Table II.7a. Mean predicted disease parameter values of rice blast on Jin heung cultivar at Icheon, South Korea under five hypothetical temperature increments using best models of maximum and final lesion numbers, and panicle blast incidence in combined datasets.[a]

Disease parameter[b]	Nitrogen (kgN/ha)	Temperature increments				
		+0 C	+1 C	+2 C	+3 C	+4 C
ML	110	50.8 aB	45.5 abB	34.0 bcB	20.0 cB	7.8 dB
	220	146.5 aA	134.9 abA	106.3 bcA	74.9 cA	31.5 dA
FL	110	13.9 aB	13.5 aB	9.7 abB	5.2 bB	2.1 cB
	220	54.1 aA	52.6 aA	40.7 abA	27.4 bA	13.6 cA
PBI	110	26.7 abB	23.1 bB	25.9 abB	29.6 aB	30.2 aB
	220	67.6 abA	65.1 bA	73.1 abA	82.5 aA	84.1 aA

[a]Values shown are means of 20 year disease predictions using simulated weather data. Means followed by the same letters are not significantly different at P= 0.05 according to Tukey-Kramer test. Upper case letters are for comparison across nitrogen treatments and lower case across temperature increments.
[b]ML= Maximum lesion number; FL= final lesion number; PBI= percent panicle blast incidence.

Table II.7b. Mean predicted disease parameter values of rice blast on IR50 and C22 cultivars at Cavinti, Laguna, Philippines under five hypothetical temperature increments in three sowing dates using best models for percent maximum and final diseased leaf area, and panicle blast severity.[a]

Disease parameter[b]	Sowing date[c]	Nitrogen (kgN/ha)	Temperature increments				
			+0 C	+1 C	+2 C	+3 C	+4 C
Cultivar: IR50							
MDLA	Feb 15	110	80.9 aB3	80.5 abB3	80.2 bcB3	79.8 cdB3	79.5 dB3
		220	82.4 aA3	82.0 abA3	81.7 bcA3	81.3 cdA3	81.0 dA3
	Jun 15	110	83.6 aB1	83.1 abB1	82.7 bcB1	82.2 cdB1	81.8 dB1
		220	85.1 aA1	84.7 abA1	84.2 bcA1	83.8 cdA1	83.3 dA1
	Oct 15	110	82.3 aB2	81.9 abB2	81.5 bcB2	81.1 cdB2	80.7 dB2
		220	83.8 aA2	83.4 abA2	83.0 bcA2	82.6 cdA2	82.2 dA2
FDLA	Feb 15	110	14.4 aA3	14.6 aA3	15.1 aA3	15.2 aA3	15.2 aA3
		220	15.3 aA3	15.6 aA3	16.1 aA3	16.1 aA3	16.2 aA3
	Jun 15	110	56.4 aA1	52.8 aA1	50.9 aA1	48.5 aA1	46.1 aA1
		220	57.8 aA1	54.2 aA1	52.3 aA1	50.0 aA1	47.5 aA1
	Oct 15	110	35.5 aA2	34.0 aA2	34.0 aA2	33.4 aA2	32.4 aA2
		220	36.6 aA2	35.2 aA2	35.2 aA2	34.7 aA2	37.9 aA2
PBS	Feb 15	110	84.7 aA1	84.7 aA1	84.7 aA1	84.7 aA1	84.7 aA1
		220	82.0 aB1	82.0 aB1	82.0 aB1	82.0 aB1	82.0 aB1
	Jun 15	110	70.3 aA2	70.3 aA2	70.3 aA2	70.3 aA2	70.3 aA2
		220	68.0 aB2	68.0 aB2	68.0 aB2	68.0 aB2	68.0 aB2
	Oct 15	110	62.6 aA3	62.6 aA3	62.6 aA3	62.6 aA3	62.6 aA3
		220	60.5 aB3	60.5 aB3	60.5 aB3	60.5 aB3	60.5 aB3

Table II.7b. (continued)

Disease parameter	Sowing date	Nitrogen (kgN/ha)	Temperature increment				
			+0 C	+1 C	+2 C	+3 C	+4 C
Cultivar: C22							
MDLA	Feb 15	110	10.1 dA2	20.4 cA2	25.3 bcA2	37.3 abA2	52.4 aA2
		220	11.1 dA2	18.0 cA2	27.5 bcA2	40.4 abA2	55.9 aA2
	Jun 15	110	31.2 dA1	43.7 cA1	58.0 bcA1	64.5 abA1	68.0 aA1
		220	33.8 dA1	46.7 cA1	58.2 bcA1	66.0 abA1	68.4 aA1
	Oct 15	110	5.9 dA3	9.3 cA3	14.1 bcA3	20.4 abA3	28.3 aA3
		220	6.4 dA3	10.1 cA3	15.3 bcA3	22.0 abA3	30.2 aA3
FDLA	Feb 15	110	2.1 dA2	2.7 cdA2	4.0 bcA2	6.6 abA2	11.8 aA2
		220	2.0 dA2	2.5 cdA2	3.6 bcA2	5.9 abA2	10.7 aA2
	Jun 15	110	7.2 dA1	9.7 cdA1	15.3 bcA1	30.2 abA1	54.8 aA1
		220	6.9 dA1	9.1 cdA1	14.1 bcA1	27.9 abA1	51.8 aA1
	Oct 15	110	14.4 dA1	15.9 cdA1	18.4 bcA1	22.7 abA1	28.9 aA1
		220	13.9 dA1	15.3 cdA1	17.6 bcA1	21.5 abA1	27.6 aA1
PBS	Feb 15	110	47.6 aA1	47.6 aA1	47.6 aA1	47.6 aA1	47.6 aA1
		220	54.4 aA1	54.4 aA1	54.4 aA1	54.4 aA1	54.4 aA1
	Jun 15	110	16.4 aA2	16.4 aA2	16.4 aA2	16.4 aA2	16.4 aA2
		220	19.0 aA2	19.0 aA2	19.0 aA2	19.0 aA2	19.0 aA2
	Oct 15	110	2.7 aA3	2.7 aA3	2.7 aA3	2.7 aA3	2.7 aA3
		220	2.9 aA3	2.9 aA3	2.9 aA3	2.9 aA3	2.9 aA3

Table II.7b. Footnotes

[a]Values shown are means of 20 year disease predictions using simulated weather data. Means followed by the same letters and numbers are not significantly different at P= 0.05 according to Tukey-Kramer test. Upper and lower case letters are for comparison across nitrogen treatments and temperature increments, respectively, while numbers are for comparison across sowing dates.
[b]MDLA= Percent maximum diseased leaf area; FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.
[c]Sowing dates were hypothetically determined to represent dry, wet, and wet-dry season plantings at the site. Feb= February; Jun= June; Oct= October.

Table II.7c. Mean predicted disease parameter values of rice blast on IR50 cultivar at the IRRI blast nursery, Philippines under five hypothetical temperature increments in three sowing dates using best models for percent final diseased leaf area and panicle blast severity.[a]

Disease parameter[b]	Sowing date[c]	Temperature increments				
		+0 C	+1 C	+2 C	+3 C	+4 C
FDLA	Feb 15	58.3 bC	66.6 aC	66.6 aC	66.6 aC	66.6 aC
	Jun 15	82.7 bA	82.7 aA	82.7 aA	82.7 aA	82.7 aA
	Oct 15	65.3 bB	76.7 aB	81.8 aB	81.8 aB	82.0 aB
PBS	Feb 15	62.0 aB	60.7 aB	54.1 bB	49.5 cB	46.4 cB
	Jun 15	76.4 aA	63.3 aA	55.9 bA	50.8 cA	47.5 cA
	Oct 15	75.1 aA	72.3 aA	61.7 bA	54.6 cA	47.9 cA

[a]Values shown are means of 20 year disease predictions using simulated weather data. Means followed by the same letters are not significantly different at P= 0.05 according to Tukey-Kramer test. Upper and lower case letters are for comparison across sowing dates and temperature increments, respectively.
[b]FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.
[c]Sowing dates were hypothetically determined to represent dry, wet, and wet-dry season plantings at the site. Feb= February; Jun= June; Oct= October.

Table II.7d. Mean predicted disease parameters values of rice blast on C22 cultivar at Gunung Medan and Sitiung, West Sumatra, Indonesia under five hypothetical temperature increments in three sowing dates.[a]

Disease parameter[b]	Sowing date[c]	Temperature increments				
		+0 C	+1 C	+2 C	+3 C	+4 C
Gunung Medan						
PBIn	Feb 15	6.2 aA	6.2 aA	6.2 aA	6.2 aA	6.2 aA
	Jun 15	3.3 aC	3.3 aC	3.3 aC	3.3 aC	3.3 aC
	Oct 15	5.2 aB	5.2 aB	5.2 aB	5.2 aB	5.2 aB
Sitiung						
FLBIn	Feb 15	6.8 aB	6.8 aB	6.8 aB	6.8 aB	6.8 aB
	Jun 15	7.4 aA	7.4 aA	7.4 aA	7.4 aA	7.4 aA
	Oct 15	6.2 aC	6.2 aC	6.2 aC	6.2 aC	6.2 aC
PBIn	Feb 15	4.6 aC	4.5 abC	4.4 bC	4.3 cC	4.3 cC
	Jun 15	6.4 aB	5.0 abB	4.5 bB	4.4 cB	4.4 cB
	Oct 15	9.2 aA	6.1 abA	4.8 bA	4.5 cA	4.5 cA

[a]Values shown are means of 20 year disease predictions using simulated weather data. Means followed by the same letters are not significantly different at P= 0.05 according to Tukey-Kramer test. Upper and lower case letters are for comparison across sowing dates and temperature increments, respectively.
[b]FLBIn= Final leaf blast index; PBIn= panicle blast index.
[c]Sowing dates were hypothetically determined to represent dry, wet, and wet-dry season plantings at the site. Feb= February; Jun= June; Oct= October.

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CHAPTER III
EXPLORING CAUSAL RELATIONSHIPS OF WEATHER TO RICE BLAST VIA PATH COEFFICIENT ANALYSIS

ABSTRACT

Path coefficient analysis was used to determine the direct and indirect effects of meteorological factors highly correlated with rice blast parameters on cultivars planted at five Asian sites. Number (DRH80) and consecutive days (CDRH80) with relative humidity ≥ 80 % had large direct effects on lesion number on leaves and panicle blast incidence at Icheon, South Korea. At Cavinti, Philippines, temperature, rainfall, and wind speed factors had direct effects on leaf and panicle blast on IR50 and C22 but the type of factors directly involved in disease development differ between these cultivars. Number of days with maximum temperature above 25 C (DG25C) and CDRH80 had the largest positive direct effects on leaf and panicle blast on IR50 at the IRRI blast nursery, Philippines. Different factors directly influenced panicle blast on the C22 cultivar at two Indonesian sites. Precipitation frequency had the largest absolute direct effect on panicle blast at Gunung Medan. Number of days with mean temperature at 20-27 C (DOPT) had the greatest direct effect at Sitiung on both leaf and panicle blast.

INTRODUCTION

Techniques for forecasting rice blast disease in temperate and tropical rice growing areas have been developed and documented elsewhere. Whether such strategies can actually be used in large-scale predictions in developing countries remains to be determined. Campbell and Madden (1990) gave six factors contributing to failure of forecasting systems: grower attitudes towards unnecessary risks in control decisions issued by forecasters, equipment and labor requirements, costs, inconvenience to usual farm operations, weather-specific implementation of control decisions, and consequent effects on non-target organisms. Spray schedules issued by forecasters are sometimes not followed in the field because time-specific applications do not always coincide with days when application is possible (Decker et al., 1986; Royle and Shaw, 1988).

Developing sound forecasting systems for rice blast that consider the behavior of the pathogen, *Pyricularia grisea* (Cooke) Sacc. (Rossman et al., 1990), under changing environments is highly desirable. In Japan, blast forecasters primarily consider inoculum intensity as determined by spore trap and plant predisposition (Yamaguchi, 1970). The predisposition method relates biological and ecological characteristics of plants to disease progression and degree of occurrence. In Thailand, spore trapping has been established in blast-prone sites using trap plants instead of spore samplers (personal communication, A. Surin, Department of Agriculture, Thailand). The disease severity on the susceptible cultivar used as the trap plant is measured and effects of environment on variations in severity analyzed. In a study conducted in the Philippines, results revealed variations in spore catch from trap plants and from electronic and conventional spore samplers due to weather effects (Pinnschmidt et al., 1993). Similarly, viability of *P. grisea* conidia from one trap method to another varied primarily because of variations in the environment to which spores were exposed prior to sampling (Bonman et al., 1987; Pinnschmidt et al., 1993). In blast areas of India, forecasting had used information extracted from planting susceptible cultivars at different times for several years (Chaudhary and Vishwadhar, 1988; Padhi and Chakrabarti, 1981). Manibhushanrao and co-workers (1989) studied further the effects of continuous planting of susceptible cultivars and weather on population structure of *P. grisea* to improve existing forecasting methodologies in India (Manibhushanrao et al., 1989).

The relationship of weather to above-canopy spore density and plant predisposition to infection has been explored with the aid of computer modeling. Several statistical techniques have been used to come up with reliable predictions. Models developed in Japan (Chiba, 1988; Ishiguro, 1991; Ishiguro and Hashimoto, 1988, 1989;

Uehara et al., 1988) are to date the most extensive rice blast forecasting packages. Deterministic mathematical functions that relate weather to leaf blast development via regression analysis, and stochastic probability models for panicle blast are used to improve understanding of pathosystem dynamics. In Korea, a computerized blast forecasting system has also been implemented. The framework is based on the relationship between aerial intensity of spores, leaf blast infection, and meteorological (weather) variables as revealed by regression analysis (Kim, 1987; Kim and Kim, 1991; Kim et al., 1987; Kim et al., 1988; Lee et al., 1989). Regression analysis has also been applied to derive forecasting models in Iran (Izadyar and Baradaran, 1990), the Philippines (El Refaei, 1977), India (Manibhushanrao et al., 1989; Tilak, 1990), China (Zhejiang Research Group, 1986), and Taiwan (Tsai, 1986).

Most blast forecasting models relate weather factors to occurrence and development of disease by statistical procedures. Choice of weather factors best influencing epidemic development is necessary for success in applying forecasting schemes to wide-scale production areas. Path coefficient analysis is a technique in multivariate regression that is potentially useful in choosing for these factors. It can identify direct and indirect effects of weather factors on disease without the confounding influences caused by multicollinearity. The analysis has two major components: the path diagram, and the decomposition of observed correlations into a sum of path coefficient terms representing simple and compound paths (Johnson and Wichern, 1992). These features enable measurement of the direct and indirect influences of one variable upon another. Mohanty et al. (1983), and Torres and Teng (1993), respectively, used path analysis to investigate the relationship between leaf characters and blast incidence, and the influence of blast on yield. The studies done in other pathosystems such as the dry beans-sheath blight (Van Bruggen and Arneson, 1986) and pepper-Phytophthora blight pathosystems (Bowers et al., 1990) revealed the usefulness of this analysis in epidemiology. Path coefficient analysis is, therefore, used in this study as a method to categorize the kind and magnitude of effect that weather factors exert on blast severity and incidence; and to demonstrate the effectiveness of this analysis in choosing the factors directly influencing the disease for use in disease forecasting.

MATERIALS AND METHODS

Disease databases. Measurements of leaf and panicle blast on susceptible cultivars were obtained at Icheon in South Korea, Cavinti and the International Rice Research Institute (IRRI) blast nursery in the Philippines, and Gunung Medan and Sitiung in Indonesia. Leaf blast data from Icheon in the form of lesion numbers on cultivar Jin heung treated with two nitrogen treatments at 110 and 220 kgN/ha were provided by Dr. C.K. Kim of Rural Development Administration (RDA) in Suweon, South Korea. Data were recorded at several assessment dates throughout the growing season during 1974-1989 plantings, along with panicle blast incidence which was measured at maturity. At Cavinti, blast data were taken from replicated upland experiments conducted during 1992-1993 using various nitrogen treatments of 60, 80, 120, and 240 kgN/ha. Percent diseased leaf area (DLA) on C22 and IR50 cultivars was recorded at several assessment dates starting from disease onset to crop maturity using a disease key (Kingsolver et al., 1984). Panicle blast severity (PBS) was likewise assessed from the two cultivars at maturity. At the IRRI blast nursery, IR50 was used to gather information on blast disease with sowings made at different times of the year during 1989-1992. DLA was recorded at various dates beginning 13 days after sowing (DAS), while PBS was recorded at crop maturity. Leaf and panicle blast indices on C22 cultivar during 1980-1981 at

Gunung Medan and 1981-1982 at Sitiung, Indonesia were provided by Mr. S. Darwis of the Sukarami Research Institute for Food Crops (SARIF) in Indonesia. The cultivar was sown at various dates with leaf and panicle blast scores recorded at 68 and 100 DAS, respectively.

Meteorological databases. Daily weather data were obtained for the sites during the years blast disease was recorded. For Icheon, daily data of maximum, minimum, and mean temperatures in C, rainfall in mm/day, mean relative humidity in percent, wind speed in m/s, sunshine hours, and solar radiation in MJ/m^2 from May to August were available during 1974-1989. The 1986-1989 rainfall and wind speed values, however, were extrapolated through simulation by a weather generator SIMMETEO (Geng et al., 1988) due to missing observations. Cavinti 1992-1993 and IRRI blast nursery 1989-1992 weather databases also contained the same variables as that of Icheon, except for sunshine hours which Cavinti did not have. The database used for the IRRI blast nursery was that taken from the IRRI wetland weather station. Daily values of weather variables for the two Indonesian sites during 1980-1982 were entirely extrapolated from monthly mean values by simulation because monthly values were the only available information. Simulation was likewise carried out by SIMMETEO program. Available weather variables for the two Indonesian sites were the same as in Icheon except wind speed and sunshine hours.

WINDOW PANE analysis. WINDOW PANE program version W1B00003 (Calvero and Coakley, 1993, unpublished) was employed to identify meteorological factors highly correlated with blast. Following the procedures in previous versions of the program (Coakley et al., 1982, 1985, 1988a, 1988b), various factors were calculated (Table III.1) from the weather databases using specific time frames (window sets) that moved across the weather database following certain duration in days beginning on, before, or after the onset of planting. Each window set contained 9 window subsets, the first being the full length window, and the others being progressively smaller subsets (Fig. III.1).

For WINDOW PANE analysis, the initial window started 24 days before transplanting (DBT) at Icheon; 30 days before sowing (DBS) at Cavinti, the IRRI blast nursery, and Sitiung; and 29 DBS at Gunung Medan (Fig. III.1). The discrepancies in the initial windows were due to limitations of available data from the weather database. At Icheon, Cavinti, and the Indonesia sites, the databases did not run in full year data (a full year weather database has 1-365 or 1-366 days). Initial movement of windows was set 10 days forward across the database for all sites, except for Icheon whose set moved four days. Similarly, time lengths of each subset windows were initially set 10 days apart, i.e., the smallest and full-length subsets were 10 and 90 days long, respectively, except for Cavinti which were set 8 days apart with smallest and full-length subsets at 6 and 70 days, respectively. For each window set, factor values were calculated and their correlation with blast parameters obtained. Meteorological factors giving highly significant correlation coefficients at $P \leq 0.05$ with blast severity or incidence were further analyzed using subset lengths adjusted to time period intervals of one day to identify the precise duration that gives the highest correlation with disease.

Choice of meteorological factors. Factors found by WINDOW PANE to be correlated with blast disease were further screened if these factors occurred before disease observation. For leaf blast, selection was directed to factors having durations that began on, before, or after planting, covering the assumed disease onset (i.e. 7 days before initial lesions were recorded), and lasted up to 45 days after planting. This was to ensure that control decisions toward leaf blast could be made early enough in case a severe maximum or final leaf blast severity is predicted. If the cut-off was set later than 45 days, control decisions could be too late to be effective in managing leaf blast. For panicle blast, weather factors with starting durations on, before, or after planting and lasted at flowering stage of the crop (i.e. 30 days before estimated maturity (Yoshida, 1981)) were selected.

Path coefficient analysis. Each meteorological factor found by WINDOW PANE to be correlated with blast consisted of a certain number of variables. Each variable represented the factor for a specific starting window and duration in days; e.g. variables for the total precipitation factor correlated with panicle blast at a site had starting windows at 19 DBS, 9 DBS, 1 DAS, 1 DAS, and 11 DAS with 80, 71, 62, 60, and 58 days duration, respectively. A weather factor variable giving the highest correlation coefficient was then selected as an independent variable in path coefficient analysis. Blast parameters such as maximum and final lesion numbers on leaves, maximum and final DLA, and panicle blast incidence and severity served as dependent variables.

Path analysis revolves around the path diagram (Figs. III.2a-d). In this study, meteorological factors (WF) (independent variables) were visualized to influence disease parameters (DP) (dependent variables) directly. The magnitude of effect was given by the partitioning of correlation coefficient (R) into direct (P) and indirect path coefficient values (R-P). Decomposition of R into P for a dependent variable (y) and two independent variables, x_1 and x_2 (Johnson and Wichern, 1992) is shown as:

$$P_1y = (w * Ryx_1) + (z * Ryx_2), \text{ for } x_1$$

$$P_2y = (z * Ryx_1) + (w * Ryx_2), \text{ for } x_2$$

where, P_1y and P_2y are the direct path coefficients for y with x_1 and x_2, respectively, and Ryx_1 and Ryx_2 are the correlation coefficients of y with x_1 and x_2, respectively. The terms, w and z were calculated as:

$$w = \frac{1}{(1 - Rx_1x_2{}^2)}$$

$$z = w * (-Rx_1x_2)$$

where Rx_1x_2 is the correlation coefficient between x_1 and x_2.

RESULTS

Correlation analysis. In general, several weather (meteorological) factors (WF) were found highly correlated with blast disease parameters (DP) by WINDOW PANE at the five Asian sites. At Icheon, only one factor was linearly related to panicle blast incidence recorded from plants treated with nitrogen (N) level of 110 kgN/ha. At Gunung Medan, no meteorological factor satisfied the rules set up in choosing factors influencing leaf blast with predictive characteristics. Thus, these particular parameters at Icheon and Gunung Medan were not included in path coefficient analysis.

Lowest correlation coefficients (R) between meteorological factors and rice blast were found at the IRRI blast nursery. The highest coefficient (R= 0.58) was given by the number of days with maximum temperature greater than 25 C (DG25C) correlated with final DLA (Table III.2a). On the other hand, highest R was observed at Gunung Medan; precipitation frequency (PFREQ) and consecutive days with precipitation (CDWP) gave the highest R values for this site (Table III.2b).

Number of days (DRH80) and consecutive days (CDRH80) with relative humidity (RH) ≥ 80 % had the highest correlation with leaf and panicle blast at all N levels at Icheon (Table III.2c). In particular, CDRH80 had the highest positive correlation (R= 0.84) with final leaf blast lesion number at low N level. At Cavinti, average minimum temperature (MMIN), DG25C, average wind speed (MWS), and number of days with wind speed ≥ 3.5 m/s (DWS35) showed highest correlation with disease parameters on cultivars IR50 and C22 (Table III.2d). Number of days with mean temperature range of 20-27 C (DOPT) and average maximum temperature (MMAX) had highest correlation with leaf and panicle blast indices, respectively, at Sitiung (Table III.2b).

Path coefficient analysis. Path analysis revealed that the highest correlation coefficient produced the largest absolute direct effects of factors on blast at Icheon (Table III.4a). Among the factors correlated with leaf blast, CDRH80 had both high correlation coefficient (R= 0.71) and large positive direct effect (Py= 0.59) on maximum leaf blast lesion number at high N level (Fig. III.2a; Table III.4a). Similarly, this factor had the largest positive direct influence on final leaf blast lesion number at low N level (Py= 0.67) but a negative direct influence on panicle blast incidence at high N level (Py= -0.86) (Fig. III.2a; Table III.4a). With maximum leaf blast lesion number at low N level, average sunshine duration (MSD) had the largest negative direct effect (Py= -0.94) (Fig. III.2a; Table III.4a). The humidity factor, DRH80 exerted the largest direct influence on final leaf blast lesion number at high N at Icheon.

At Cavinti and the IRRI blast nursery, high correlation did not necessarily mean high direct effect on blast. Maximum DLA and panicle blast severity on C22 at Cavinti produced high correlation with DWS35 and CDOPT (consecutive days with mean temperature range of 20-27 C), respectively. The largest absolute direct effects, however, were given by total precipitation (TPREC) on maximum DLA and MMAX on panicle blast (Fig. III.2b; Table III.4b). On IR50 at Cavinti, MMIN showed the largest positive direct effect on both maximum and final DLA, while consecutive days without precipitation (CDWOP) produced a similar magnitude of influence on panicle blast severity (Fig. III.2b; Table III.4b). At the nursery, although highest correlation with final DLA and panicle blast severity was given by DG25C factor, CDRH80 exerted the largest direct effect (Py= 0.74) on panicle blast (Fig. III.2c; Table III.4c).

Rainfall factors, PFREQ and CDWP gave the same correlation coefficient with panicle blast index at Gunung Medan. However, PFREQ had the largest positive effect (Py= 0.84) than CDWP (Py= 0.78) on this disease parameter (Fig. III.2d; Table III.4d). At Sitiung, temperature factors were found having direct influences on panicle blast. The factor, DOPT had the largest negative direct influence (Py= -0.71) (Fig. III.2d) on this parameter even though MMAX gave the highest correlation value at R= -0.81 (Table III.4d). DOPT also exerted the largest negative direct effect (Py= -0.48) on final leaf blast index at Sitiung.

DISCUSSION

The data from all sites, except Icheon, showed that high correlation of weather factors with disease may or may not have large direct effects on blast. The actual relationship of environment with disease is, therefore, not thoroughly explained by correlation analysis.

Relative humidity (RH) factors CDRH80 and DRH80 both had the highest correlation and largest direct influences on leaf (expressed as lesion number) and panicle blast incidence at Icheon (Table III.4a). Sunshine duration showed a greater effect on maximum lesion number at low nitrogen level than at high nitrogen level (Table III.4a). In Korea, the *P. grisea* season usually lasts from mid-June to early August when humidity and rainfall are high and the temperature range is at 20-30 C (Kim and Kim, 1991). Studies on temperate blast epidemics have shown that temperature beyond 27 C slows down or totally inhibits colonization and spread of *P. grisea* within host tissues and reduces the sporulation potential of lesions (Kato, 1974; Kato, 1976; Kato and Kozaka, 1974; Suzuki, 1975). Likewise, heavy rainfall, especially amounts beyond 83 mm/day may wash off spores from leaves or in the air (Suzuki, 1975), thereby decreasing the success of secondary cycles to provide inoculum for further spread. These observations support why high humidity triggers successful blast outbreaks during the cropping months at Icheon than rainfall or temperature.

The level of influence of weather factors on disease at different N levels at Icheon gave no distinct trend. Obviously, weather and nitrogen exert distinct effects on disease severity and progression, and severe disease may be possible at optimum weather conditions even at low N level. In general, blast is most severe under high N and optimum weather conditions (KÜrschner et al., 1990).

At Cavinti, blast is influenced by three weather variables: temperature, rainfall, and wind speed (Table III.4b). The cultivars IR50 and C22, although both are susceptible to blast, require different weather factors for disease to develop. Such a discrepancy between these cultivars is attributed to the direct influence of weather (especially temperature) on predisposition of host to pathogen attack, differences in host canopy structure, and specific climatic requirements of races attacking the host. IR50 is a lowland wet rice cultivar that is not well adapted to grow in upland ecosystems, while C22 was bred for dry, upland cultivation. At Cavinti, the study was conducted under upland conditions; extreme temperature ranges, therefore, affected the reaction of IR50 to blast more than C22.

The large direct influence of wind speed on leaf blast on C22 can be attributed to canopy structure. This cultivar has broader leaves and taller canopy height than IR50. The amount of spores caught on leaves is, therefore, higher in C22 than in IR50 because of large surface area of C22. Blast infection was, however, relatively severe in IR50 probably because of reduced resistance caused by either host predisposition or the dominant pathogen races/lineages occurring at the site which were capable of infecting IR50. Preliminary studies characterizing *P. grisea* lineages at Cavinti showed that IR50 is infected by a pathogen lineage different from that infecting C22 (Dahu, 1993). This difference in lineages would also explain why different weather factors were reported to influence leaf blast severity on IR50 and C22. This difference is also shown by infections on the panicles. Maximum temperature (MMAX) had the largest negative direct effect on panicle blast on C22, while on IR50, consecutive days without rainfall (CDWOP) was observed to have a positive influence. The kind of effect exerted by MMAX on C22 panicle blast is similar to that in leaf infection where reduction in severity is observed with increasing temperature (El Refaei, 1977; Kato, 1974; Kato and Kozaka, 1974; Suzuki, 1975). On IR50, the positive effect of CDWOP on panicle blast is a result of the absence of heavy rainfall. Suzuki (1975) reported that rainfall of large amount (i.e. $\geq$ 83 mm/day) actually reduces the possibility of deposited spores to get established in panicle tissues because it tends to wash-off these spores from these tissues. Once this happens, panicle infection is reduced. In another situation, drizzling rain has shown to favor leaf and panicle blast because of the moisture provided for infection (Kato, 1976).

The magnitude of weather effects at the IRRI blast nursery was relatively not high (Table III.4c). Similarly, correlation coefficients of factors to disease were also low (Table III.2a). These may happen because there was no clear linear relationship observed between blast and weather factors at the nursery. Leaf and panicle blast were always severe at this site even at non-optimum conditions for disease development. Likewise, inoculum source was always present in the area, and infection, although not induced, was regarded as artificially induced. Nevertheless, DG25C and CDRH80 were found to be exerting the largest direct effects on final DLA and panicle blast, respectively.

A positive effect by DG25C on leaf blast at the IRRI nursery appears to be biologically incorrect if its influence is directed to the life stages of *P. grisea.* Since the relationship suggests increasing severity with increasing number of days with maximum temperature beyond 25 C, this is contrary to what has been reported on the effect of temperature on leaf blast. Another possibility that may be biologically valid is that temperature affects host predisposition. As at Cavinti, IR50 at the nursery was planted under upland conditions. Since IR50 is not adapted to these conditions, high temperature may easily predispose this cultivar to severe pathogen infection. The factor CDRH80, on the other hand, had a positive effect on panicle blast which appears to directly affect *P. grisea* life stages. Such an effect supports previous studies on the influence of humidity on panicle blast pathosystem (Ishiguro and Hashimoto, 1988, 1989).

Opposing effects of factors on panicle blast were observed from the two Indonesia sites. Most temperature factors had positive influences on this parameter at Gunung Medan as opposed to negative influences at Sitiung (Table III.4d). The majority of temperature factors at Sitiung occurred earlier in the growing season than factors at Gunung Medan (Table III.3b). It appears that at Sitiung, the negative influence of temperature on panicle blast is actually due to the inhibitory effect of increasing temperature on leaf blast. It has been shown that although no direct relationships occur between leaf and panicle blast pathosystems (personal communication, Jose Bandong, IRRI; Teng et al., 1991), lesions on the leaves are potential sources of inoculum for panicle infection (Ishiguro and Hashimoto, 1988, 1991). When temperature is unfavorable for leaf blast, this may result in reduced spore production, thereby reducing inoculum for panicle infection. Such a discrepancy between the two Indonesia sites could also be related to altitude difference. Sitiung is at higher altitude with low annual temperature than Gunung Medan. Host predisposition may be affected at changing altitudes in this case (personal communication, Paul S. Teng, IRRI). Similarly, the difference in the climatic requirements of the pathogen races occurring at the sites and the difference on race composition between sites may cause the discrepancy in the weather factors affecting blast at the two Indonesian sites.

At Gunung Medan, precipitation frequency (PFREQ) had a larger positive direct effect on panicle blast than consecutive days with rain (CDWP), even though they have the same level of correlation with this disease parameter (Table III.4d). In this case, the number of wet day periods is more important than if rain occurs in consecutive days. A possible reason is that PFREQ provides enough moisture for the infection process to complete. It is also possible that such moisture was present on the days it was most needed by the pathogen. When moisture becomes unavailable prior to the completion of the process, germination and subsequent host colonization may be prematurely terminated (Gunther, 1986). Although moisture is also provided by CDWP, at some point, dry periods that occurred in between days with rainfall would significantly interrupt the infection process.

The statistical approach used in this study improved the choice of weather factors highly correlated with disease to allow selection of those that are most influential in driving the epidemic. Results from path coefficient analysis suggest that only a few weather variables should be actually measured and used in predictions. The analysis benefits blast forecasting studies because it reveals the magnitude of influence that weather factors have, not only on the development of *P. grisea* and its succeeding cycles, but also on host predisposition to pathogen infection. These relationships would not be defined by using correlation analysis. Path coefficient analysis together with WINDOW PANE program, are essential in developing blast forecasting strategy so that key meteorological factors that have largest effects on disease are identified.

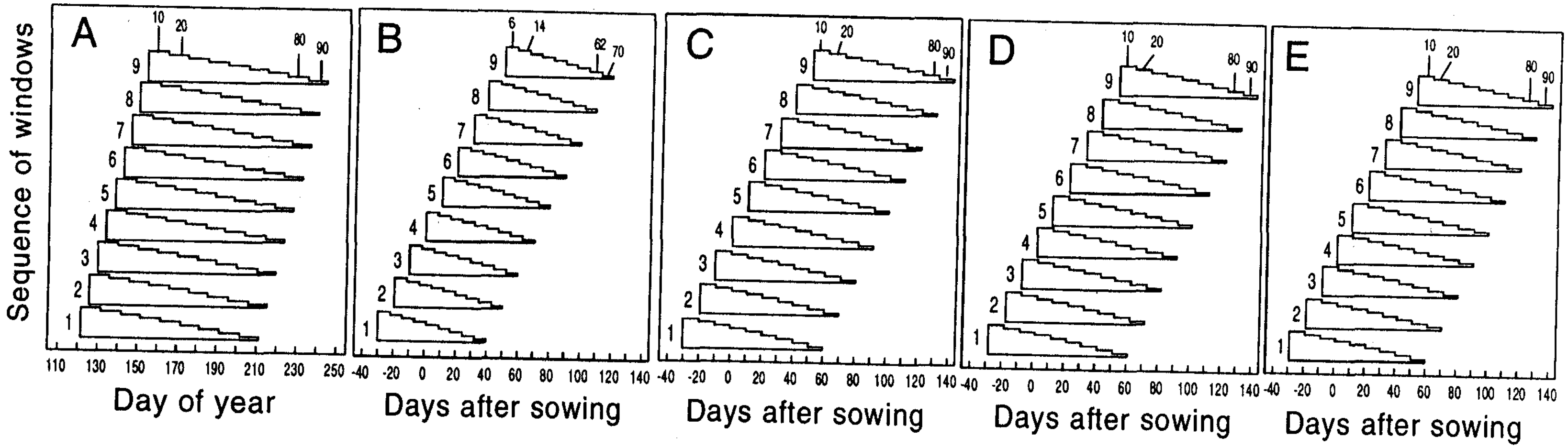

Fig. III.1. Sequence of windows showing how WINDOW PANE program generated meteorological factors for developing predictive models for **A**, Icheon, South Korea, **B**, Cavinti and **C**, IRRI blast nursery, Philippines, and **D**, Gunung Medan and **E**, Sitiung, West Sumatra, Indonesia. There are 9 window sets each having smaller subsets; e.g. window set 1 at Icheon started at DY 121 and moves four days forward to start at DY 125 for window set 2. Each set has 10 and 90 days duration for shortest and longest subsets, respectively, at this site.

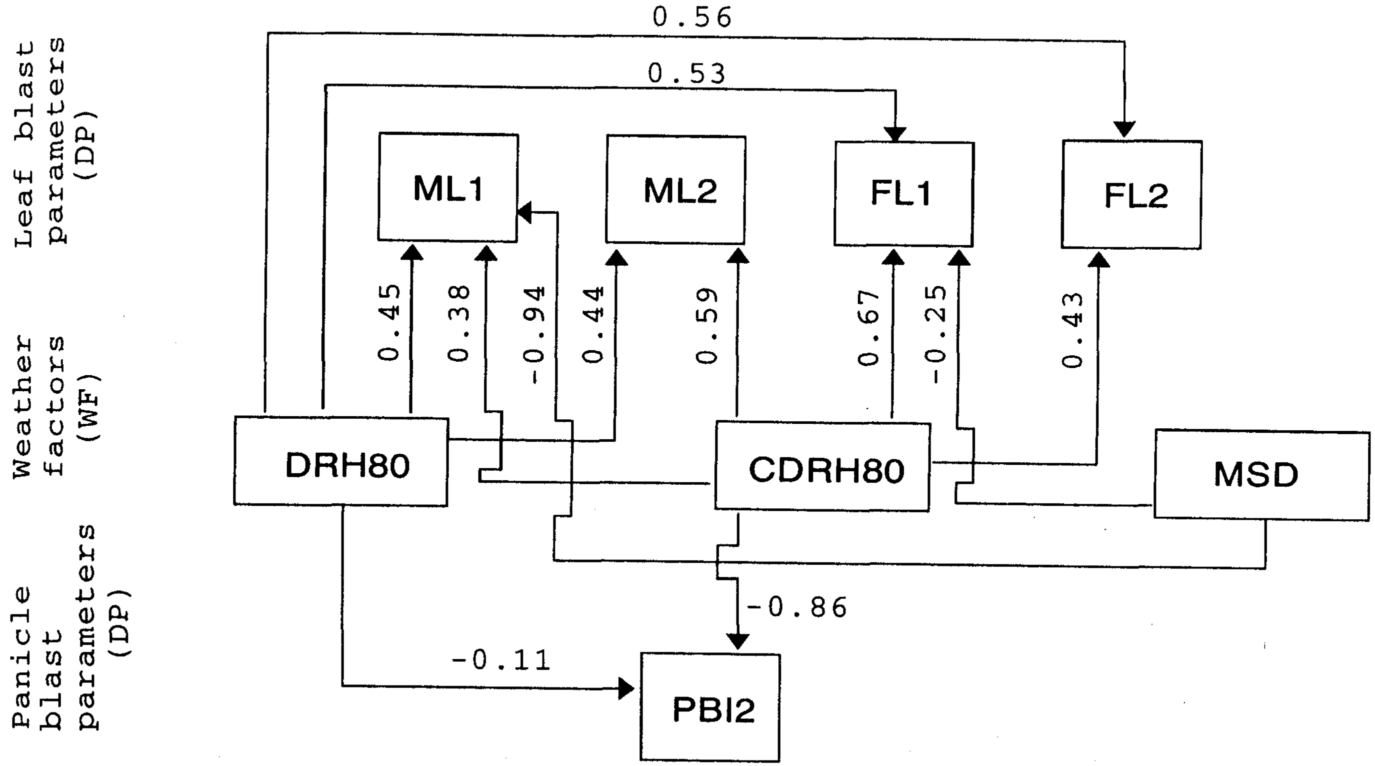

Fig. III.2a. Path of influence of meteorological factors (WF) that had the largest direct effects (Py) on blast parameters (DP) on Jin heung cultivar at Icheon, South Korea. Descriptions of weather factors are presented in Table III.1. ML1 and ML2 are maximum leaf blast lesion numbers at 110 kgN/ha and 220 kgN/ha, respectively; FL1 and FL2 are final leaf blast lesion numbers at 110 kgN/ha and 220 kgN/ha, respectively; PBI2 is panicle blast incidence (%) at 220 kgN/ha. Numbers are the path coefficient values of the direct effect.

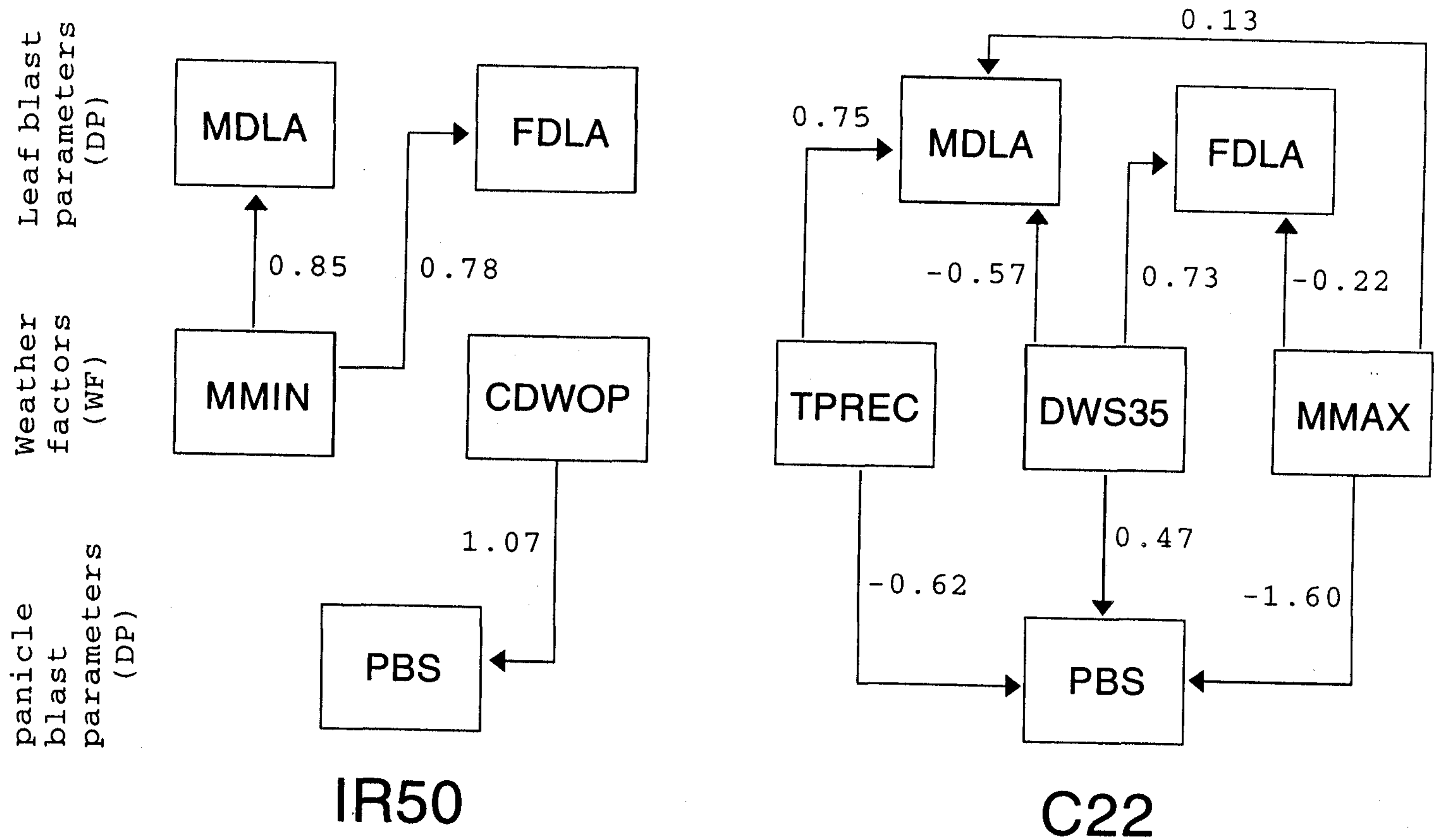

Fig. III.2b. Path of influence of weather factors (WF) that had the largest direct effects (Py) on blast parameters (DP) on IR50 and C22 cultivars at Cavinti, Laguna, Philippines. Descriptions of weather factors are presented in Table III.1. MDLA= Maximum diseased leaf area (%); FDLA= final diseased leaf area (%); PBS= panicle blast severity (%). Numbers are the path coefficient values of the direct effect.

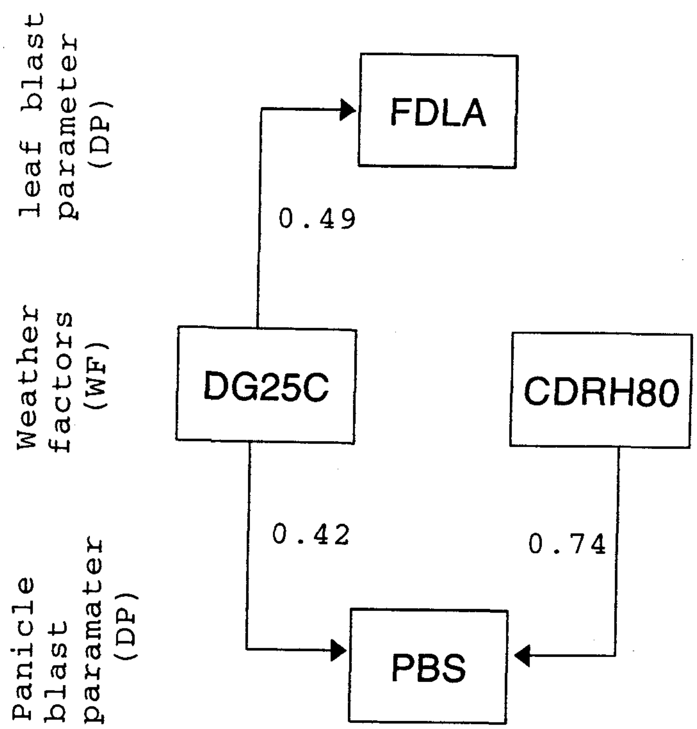

Fig. III.2c. Path of incluence of weather factors (WF) that had the largest direct effects (Py) on blast parameters (DP) on IR50 cultivar at the IRRI blast nursery, Philippines. Descriptions of weather factors are presented in Table III.1. FDLA= final diseased leaf area (%); PBS= panicle blast severity (%). Numbers are the path coefficient values of the direct effect.

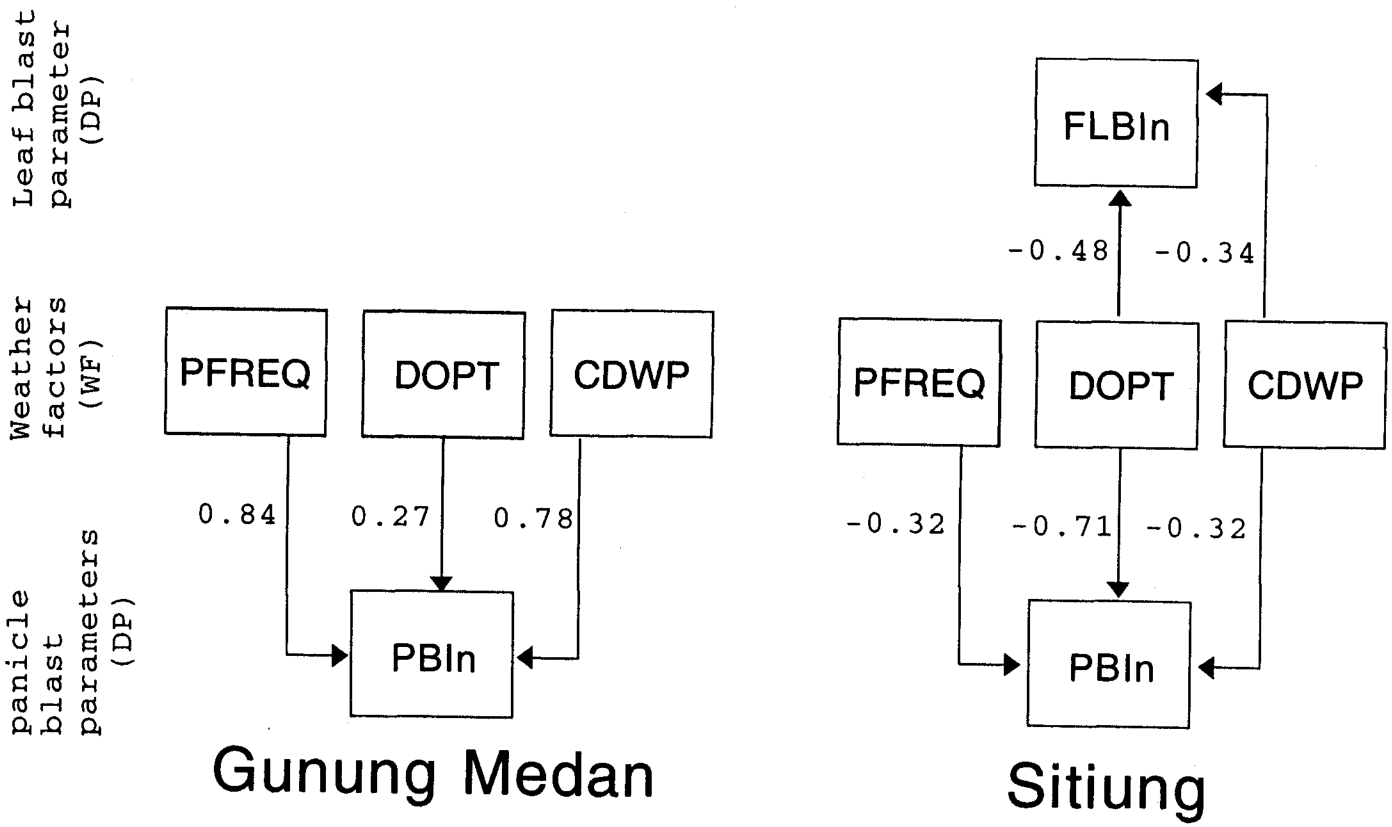

Fig. III.2d. Path of influence of weather factors (WF) that had the largest direct effects (Py) on blast parameters (DP) on C22 cultivar at Gunung Medan and Sitiung, Indonesia. Descriptions of weather factors are presented in Table III.1. FLBIn= Final leaf blast index; PBIn= panicle blast index. Numbers are the path coefficient values of the direct effect.

Table III.1. Meteorological factors considered in generating models for five sites in Asia.[a]

Factor description	Variable Name	Sites				
		Icheon	Cavinti	IRRI	G. Medan	Sitiung
Average maximum temperature (C)	MMAX	x	x	x	x	x
Average mean temperature (C)	MAVE	x	x	x	x	x
Average minimum temperature (C)	MMIN	x	x	x	x	x
Average relative humidity (%)	MRH	x	x	x	x	x
Average solar radiation (MJ/m^2)	MSR	x	x	x	x	x
Average sunshine duration (hours)	MSD	x	o	x	o	o
Average wind speed (m/s)	MWS	x	x	x	o	o
Consecutive days with mean temperature range of 20-27 C	CDOPT	x	x	x	x	o
Consecutive days with precipitation	CDWP	x	x	x	x	x
Consecutive days with relative humidity ≥ 80%	CDRH80	x	x	x	x	x
Consecutive days without precipitation	CDWOP	x	x	x	x	x
Number of days with maximum temperature > 25 C	DG25C	x	x	x	x	x
Number of days with mean temperature range of 20-27 C	DOPT	x	x	x	x	x
Number of days with precipitation ≥ 84 mm/day	DR84	x	x	x	x	x
Number of days with relative humidity ≥ 80%	DRH80	x	x	x	x	x
Number of days with wind speed ≥ 3.5 m/s	DWS35	x	x	x	x	x
Positive degree days with 7 C as base temperature	PDD	x	x	x	o	o
Positive degree days with 10 C as base temperature	PDD10	x	x	x	x	x
Precipitation frequency (days)	PFREQ	x	x	x	x	x
Total precipitation (mm/day)	TPREC	x	x	x	x	x

[a]x= Available at this site; o= not available.

Table III.2a. Correlation coefficients (R) of meteorological factors (WF) with blast parameters (DP) on IR50 cultivar at the IRRI blast nursery, Philippines.[a]

	Variables[b]								
	DP	WF1	WF2	WF3	WF4	WF5	WF6	WF7	WF8
DP: Percent final diseased leaf area									
DP	-	0.53	0.41	-0.51	0.58	-	-	-	-0.41
WF1	0.53	-	0.70	-0.84	0.30	-	-	-	-0.40
WF2	0.41	0.70	-	-0.64	0.30	-	-	-	-0.59
WF3	-0.51	-0.84	-0.64	-	-0.26	-	-	-	0.38
WF4	0.58	0.30	0.30	-0.26	-	-	-	-	-0.24
WF8	-0.41	-0.40	-0.59	0.38	-0.24	-	-	-	-
DP: Percent panicle blast severity									
DP	-	-	-	-	0.52	0.46	0.50	0.40	-
WF4	0.52	-	-	-	-	0.38	0.46	0.19	-
WF5	0.46	-	-	-	0.38	-	0.98	0.88	-
WF6	0.50	-	-	-	0.46	0.98	-	0.84	-
WF7	0.40	-	-	-	0.19	0.88	0.84	-	-

[a]Coefficients are significant at P= 0.05.
[b]Meteorological factors (WF) have different durations as presented in Table III.3a. WF1= PFREQ; WF2= CDWP; WF3= CDWOP; WF4= DG25C; WF5= DRH80; WF6= CDRH80; WF7= MRH; WF8= MWS. Descriptions of meteorological factors are presented in Table III.1.

Table III.2b. Correlation coefficients (R) of meteorological factors (WF) with blast parameters (DP) on C22 cultivar at Gunung Medan and Sitiung, West Sumatra, Indonesia.[a]

	Variables[b]														
	DP	WF1	WF2	WF3	WF4	WF5	WF6	WF7	WF8	WF9	WF10	WF11	WF12	WF13	WF14
DP: Panicle blast index at Gunung Medan[c]															
DP	-	-	0.93	0.93	-0.83	0.82	-0.68	0.74	0.73	0.74	-	0.81	0.79	0.71	-0.73
WF2	0.93	-	-	0.88	-0.95	0.82	-0.66	0.80	0.77	0.77	-	0.72	0.68	0.67	-0.65
WF3	0.93	-	0.88	-	0.79	0.71	-0.55	0.72	0.63	0.66	-	0.88	0.84	0.75	-0.59
WF4	-0.83	-	-0.95	-0.79	-	-0.73	0.54	-0.74	-0.70	-0.71	-	-0.57	-0.52	-0.43	0.60
WF5	0.82	-	0.82	0.71	-0.73	-	-0.73	0.91	0.76	0.76	-	0.68	0.67	0.61	-0.79
WF6	-0.68	-	-0.66	-0.55	0.54	-0.73	-	-0.84	-0.94	-0.94	-	-0.62	-0.64	-0.66	0.89
WF7	0.74	-	0.80	0.72	-0.74	0.91	-0.84	-	0.86	0.87	-	0.70	0.68	0.65	-0.81
WF8	0.73	-	0.77	0.63	-0.70	0.76	-0.94	0.86	-	0.99	-	0.68	0.68	0.63	-0.90
WF9	0.74	-	0.77	0.66	-0.71	0.76	-0.94	0.87	0.99	-	-	0.70	0.71	0.61	-0.93
WF11	0.81	-	0.72	0.88	-0.57	0.68	-0.62	0.70	0.68	0.70	-	-	0.99	0.84	-0.67
WF12	0.79	-	0.68	0.84	-0.52	0.67	-0.64	0.68	0.68	0.71	-	0.99	-	0.82	-0.70
WF13	0.71	-	0.67	0.75	-0.43	0.61	-0.66	0.65	0.63	0.61	-	0.84	0.82	-	-0.48
WF14	-0.73	-	-0.65	-0.59	0.90	-0.79	0.89	-0.81	-0.90	-0.93	-	-0.67	-0.70	-0.48	-
DP: Leaf blast index at Sitiung															
DP	-	-0.65	-	-0.62	-	-	-	-	-0.68	-	-	-	-	-	0.67
WF1	-0.65	-	-	0.39	-	-	-	-	0.54	-	-	-	-	-	-0.55
WF3	-0.62	0.39	-	-	-	-	-	-	0.37	-	-	-	-	-	-0.87
WF8	-0.68	0.54	-	0.37	-	-	-	-	-	-	-	-	-	-	-0.52
WF14	0.67	-0.55	-	-0.87	-	-	-	-	-0.52	-	-	-	-	-	-

Table III.2b. (continued)

	Variables														
	DP	WF1	WF2	WF3	WF4	WF5	WF6	WF7	WF8	WF9	WF10	WF11	WF12	WF13	WF14
DP: Panicle blast index at Sitiung															
DP	-	-0.73	-0.71	-0.70	0.68	-0.81	-0.65	-0.76	-0.77	-0.76	-0.80	0.66	-	-	-
WF1	-0.73	-	0.88	0.92	-0.94	0.84	0.80	0.88	0.83	0.83	0.88	-0.62	-	-	-
WF2	-0.71	0.88	-	0.84	-0.90	0.75	0.86	0.81	0.85	0.85	0.89	-0.57	-	-	-
WF3	-0.70	0.92	0.84	-	-0.94	0.73	0.76	0.81	0.83	0.83	0.76	-0.49	-	-	-
WF4	0.68	-0.94	-0.90	-0.94	-	-0.77	-0.77	-0.82	-0.89	-0.89	-0.87	0.50	-	-	-
WF5	-0.81	0.84	0.75	0.73	-0.77	-	0.83	0.93	0.68	0.66	0.82	-0.74	-	-	-
WF6	-0.65	0.80	0.86	0.76	-0.77	0.83	-	0.94	0.58	0.57	0.75	-0.85	-	-	-
WF7	-0.76	0.88	0.81	0.81	-0.82	0.93	0.94	-	0.62	0.61	0.78	-0.86	-	-	-
WF8	-0.77	0.83	0.85	0.83	-0.89	0.68	0.58	0.62	-	1.00	0.91	-0.33	-	-	-
WF9	-0.76	0.83	0.85	0.83	-0.89	0.66	0.57	0.61	1.00	-	0.91	-0.32	-	-	-
WF10	-0.80	0.88	0.89	0.76	-0.87	0.82	0.75	0.78	0.91	0.91	-	-0.62	-	-	-
WF11	0.66	-0.62	-0.57	-0.49	0.50	-0.74	-0.85	-0.86	-0.33	-0.32	-0.62	-	-	-	-

[a]Coefficients are significant at P= 0.05.
[b]Meteorological factors (WF) have different durations as presented in Table III.3b. WF1= TPREC; WF2= PFREQ; WF3= CDWP; WF4= CDWOP; WF5= MMAX; WF6= MMIN; WF7= MAVE; WF8= DOPT; WF9= CDOPT; WF10= DG25C; WF11= DRH80; WF12= CDRH80; WF13= MRH; WF14= MSR. Descriptions of meteorological factors are presented in Table III.1.
[c]There were no meteorological factors correlated with leaf blast index at Gunung Medan, thus, correlation and path coefficient analyses were done only for panicle blast index.

Table III.2c. Correlation coefficients (R) of meteorological factors (WF) with blast parameters (DP) on Jin heung cultivar at Icheon, South Korea.[a]

	Variables[b]												
	DP	WF1	WF2	WF3	WF4	WF5	WF6	WF7	WF8	WF9	WF10	WF11	WF12
DP: Maximum lesion number at 110 kgN/ha													
DP	-	0.58	-	-	-	0.62	0.61	-	-	-	-	-0.67	-0.56
WF1	0.58	-	-	-	-	0.36	0.45	-	-	-	-	-0.60	-0.54
WF5	0.62	0.36	-	-	-	-	0.92	-	-	-	-	-0.34	-0.25
WF6	0.61	0.45	-	-	-	0.92	-	-	-	-	-	-0.46	-0.40
WF11	-0.67	-0.60	-	-	-	-0.34	-0.46	-	-	-	-	-	0.97
WF12	-0.56	-0.54	-	-	-	-0.25	-0.40	-	-	-	-	0.97	-
DP: Maximum lesion number at 220 kgN/ha													
DP	-	-	-	-	-	0.62	0.71	-	-0.57	-	-	-	-
WF5	0.62	-	-	-	-	-	0.38	-	-0.39	-	-	-	-
WF6	0.71	-	-	-	-	0.38	-	-	-0.19	-	-	-	-
WF8	-0.57	-	-	-	-	-0.39	-0.19	-	-	-	-	-	-
DP: Final lesion number at 110 kgN/ha													
DP	-	0.68	-	-	-	0.81	0.84	-	-	-	-	-0.56	-
WF1	0.68	-	-	-	-	0.55	0.48	-	-	-	-	-0.57	-
WF5	0.81	0.55	-	-	-	-	0.91	-	-	-	-	-0.37	-
WF6	0.84	0.48	-	-	-	0.91	-	-	-	-	-	-0.49	-
WF11	-0.56	-0.57	-	-	-	0.37	-0.49	-	-	-	-	-	-

Table III.2c. (continued)

	Variables												
	DP	WF1	WF2	WF3	WF4	WF5	WF6	WF7	WF8	WF9	WF10	WF11	WF12
DP: Final lesion number at 220 kgN/ha													
DP	-	-	0.58	0.59	-0.57	0.64	0.63	0.57	-	-0.53	-0.58	-	-
WF2	0.58	-	-	0.97	-0.94	0.35	0.35	0.42	-	-0.40	-0.65	-	-
WF3	0.59	-	0.97	-	-0.88	0.35	0.36	0.39	-	-0.43	-0.67	-	-
WF4	-0.57	-	-0.94	-0.88	-	-0.30	-0.25	-0.39	-	0.32	0.66	-	-
WF5	0.64	-	0.35	0.35	-0.30	-	0.98	0.91	-	-0.49	-0.48	-	-
WF6	0.63	-	0.35	0.36	-0.25	0.98	-	0.86	-	-0.42	-0.37	-	-
WF7	0.57	-	0.42	0.39	-0.39	0.91	0.86	-	-	-0.52	-0.53	-	-
WF9	-0.53	-	-0.40	-0.43	0.32	-0.49	-0.42	-0.52	-	-	0.80	-	-
WF10	-0.58	-	-0.65	-0.67	0.66	-0.48	-0.37	-0.53	-	0.80	-	-	-
DP: Percent panicle blast incidence at 220 kgN/ha[c]													
DP	-	-0.70	-	-	-	-0.76	-0.79	-	-	-	-	-	-
WF1	-0.70	-	-	-	-	0.49	0.56	-	-	-	-	-	-
WF5	-0.76	0.49	-	-	-	-	0.98	-	-	-	-	-	-
WF6	-0.79	0.56	-	-	-	0.98	-	-	-	-	-	-	-

[a]Coefficients are significant at P= 0.05.
[b]Meteorological factors (WF) have different durations as presented in Table III.3c. WF1= TPREC; WF2= PFREQ; WF3= CDWP; WF4= CDWOP; WF5= DRH80; WF6= CDRH80; WF7= MRH; WF8= DOPT; WF9= MMAX; WF10= DG25C; WF11= MSD; WF12= MSR. Descriptions of meteorological factors are presented in Table III.1.
[c]Panicle blast incidence at 110 kgN/ha was not included in correlation and path coefficient analyses because only one weather factor was found correlated with this parameter.

Table III.2d. Correlation coefficients (R) of meteorological factors (WF) with blast parameters (DP) on IR50 and C22 cultivars at Cavinti, Laguna, Philippines.[a]

	Variables[b]															
	DP	WF1	WF2	WF3	WF4	WF5	WF6	WF7	WF8	WF9	WF10	WF11	WF12	WF13	WF14	WF15
DP: Percent maximum diseased leaf area on IR50																
DP	-	0.71	-	0.65	0.72	0.80	0.76	-0.64	-	-	-	-	-	-0.79	0.75	-
WF1	0.71	-	-	0.86	0.78	0.89	0.84	-0.98	-	-	-	-	-	-0.89	-0.81	-
WF3	0.65	0.86	-	-	0.62	0.74	0.70	-0.89	-	-	-	-	-	-0.81	-0.70	-
WF4	0.72	0.78	-	0.62	-	0.84	0.84	-0.76	-	-	-	-	-	-0.86	-0.95	-
WF5	0.80	0.89	-	0.74	0.84	-	0.99	-0.81	-	-	-	-	-	-0.92	-0.94	-
WF6	0.76	0.84	-	0.70	0.84	0.99	-	-0.77	-	-	-	-	-	-0.87	-0.93	-
WF7	-0.64	-0.98	-	-0.89	-0.76	-0.81	-0.77	-	-	-	-	-	-	0.85	0.76	-
WF13	-0.79	-0.89	-	-0.81	-0.86	-0.92	-0.87	0.85	-	-	-	-	-	-	0.94	-
WF14	0.75	-0.81	-	-0.70	-0.95	-0.94	-0.93	-0.76	-	-	-	-	-	0.94	-	-
DP: Percent final diseased leaf area on IR50																
DP	-	0.70	-	0.71	0.56	0.76	0.68	-0.57	-	0.54	-	0.57	0.55	-0.74	-0.68	-
WF1	0.70	-	-	0.89	0.48	0.51	0.45	-0.43	-	0.35	-	0.85	0.89	-0.68	-0.39	-
WF3	0.71	0.89	-	-	0.65	0.67	0.70	-0.38	-	0.58	-	0.54	0.66	-0.75	-0.62	-
WF4	0.56	0.48	-	0.65	-	0.86	0.88	-0.54	-	0.97	-	0.26	0.49	-0.90	-0.43	-
WF5	0.76	0.51	-	0.67	0.86	-	0.96	-0.61	-	0.90	-	0.17	0.37	-0.93	-0.79	-
WF6	0.68	0.45	-	0.70	0.88	0.96	-	-0.62	-	0.92	-	0.06	0.30	-0.85	-0.78	-
WF7	-0.57	-0.43	-	-0.38	-0.54	-0.61	-0.62	-	-	-0.45	-	-0.36	-0.55	0.51	0.41	-
WF9	0.54	0.35	-	0.58	0.97	0.90	0.92	-0.45	-	-	-	0.07	0.30	-0.89	-0.53	-
WF11	0.57	0.85	-	0.54	0.26	0.17	0.06	-0.36	-	0.07	-	-	0.96	-0.43	-0.09	-
WF12	0.55	0.89	-	0.66	0.49	0.37	0.30	-0.55	-	0.30	-	0.96	-	-0.60	-0.04	-
WF13	-0.74	-0.68	-	-0.75	-0.90	-0.93	-0.85	0.51	-	-0.89	-	-0.43	-0.60	-	0.59	-
WF14	-0.68	-0.39	-	-0.62	-0.43	-0.79	-0.78	0.41	-	-0.53	-	0.09	-0.04	0.59	-	-

Table III.2d. (continued)

	Variables															
	DP	WF1	WF2	WF3	WF4	WF5	WF6	WF7	WF8	WF9	WF10	WF11	WF12	WF13	WF14	WF15
DP: Percent panicle blast severity on IR50																
DP	-	-0.53	0.59	-	-	-	-	-0.58	-	-	-	-0.57	-0.58	-	-	0.58
WF1	-0.53	-	-0.90	-	-	-	-	0.90	-	-	-	0.95	0.89	-	-	-0.96
WF2	0.59	-0.90	-	-	-	-	-	-0.99	-	-	-	-0.99	-0.99	-	-	0.94
WF7	0.58	0.90	-0.99	-	-	-	-	-	-	-	-	0.98	0.99	-	-	-0.93
WF11	-0.57	0.92	-0.99	-	-	-	-	0.98	-	-	-	-	0.99	-	-	-0.94
WF12	-0.58	0.89	-0.99	-	-	-	-	0.99	-	-	-	0.99	-	-	-	-0.92
WF15	0.58	-0.96	0.94	-	-	-	-	-0.93	-	-	-	-0.94	-0.92	-	-	-
DP: Percent maximum diseased leaf area on C22																
DP	-	0.77	-	0.75	0.67	0.72	0.70	-0.73	-0.73	-	-	-	-	-	-0.78	0.76
WF1	0.77	-	-	0.73	0.64	0.71	0.69	-0.98	-0.98	-	-	-	-	-	-0.44	0.65
WF3	0.75	0.73	-	-	0.56	0.79	0.67	-0.61	-0.61	-	-	-	-	-	-0.67	0.35
WF4	0.67	0.64	-	0.56	-	0.94	0.99	-0.70	-0.70	-	-	-	-	-	-0.78	0.81
WF5	0.72	0.71	-	0.79	0.94	-	0.98	-0.70	-0.70	-	-	-	-	-	-0.79	0.66
WF6	0.70	0.69	-	0.67	0.99	0.98	-	-0.72	-0.72	-	-	-	-	-	-0.79	0.76
WF7	-0.73	-0.98	-	-0.61	-0.70	-0.70	-0.72	-	1.00	-	-	-	-	-	0.41	-0.72
WF8	-0.73	-0.98	-	-0.61	-0.70	-0.70	-0.72	1.00	-	-	-	-	-	-	0.41	-0.72
WF14	-0.78	-0.44	-	-0.67	-0.78	-0.79	-0.79	0.41	0.41	-	-	-	-	-	-	-0.74
WF15	0.76	0.65	-	0.35	0.81	0.66	0.76	-0.72	-0.72	-	-	-	-	-	-0.74	-
DP: Percent final diseased leaf area on C22																
DP	-	-	-	-	-0.58	-	-0.57	-	-	-0.75	-	-	-	0.75	0.75	-0.69
WF4	-0.58	-	-	-	-	-	0.99	-	-	0.84	-	-	-	-0.83	-0.84	0.87
WF6	-0.57	-	-	-	0.99	-	-	-	-	0.81	-	-	-	-0.84	-0.81	0.86
WF9	-0.75	-	-	-	0.84	-	0.81	-	-	-	-	-	-	-0.87	-1.00	0.97
WF13	0.75	-	-	-	-0.83	-	-0.84	-	-	-0.87	-	-	-	-	0.87	-0.89
WF14	0.75	-	-	-	-0.84	-	-0.81	-	-	-1.00	-	-	-	0.87	-	-0.97
WF15	-0.69	-	-	-	0.87	-	0.86	-	-	0.97	-	-	-	-0.89	-0.97	-

Table III.2d. (continued)

	Variables															
	DP	WF1	WF2	WF3	WF4	WF5	WF6	WF7	WF8	WF9	WF10	WF11	WF12	WF13	WF14	WF15
DP: Percent panicle blast severity on C22																
DP	-	-0.83	-	-0.69	-0.73	-0.57	-0.68	-0.68	-0.82	0.85	-	-	-	0.72	0.63	-
WF1	-0.83	-	-	0.67	0.53	0.31	0.49	0.65	0.65	-0.89	-	-	-	-0.68	-0.38	-
WF3	-0.69	0.67	-	-	0.50	0.36	0.47	0.61	0.34	-0.61	-	-	-	-0.66	-0.41	-
WF4	-0.73	0.53	-	0.50	-	0.97	0.99	0.91	0.90	-0.40	-	-	-	-0.92	-0.99	-
WF5	-0.57	0.31	-	0.36	0.97	-	0.98	0.86	0.80	-0.17	-	-	-	-0.86	-0.99	-
WF6	-0.68	0.49	-	0.47	0.99	0.98	-	0.98	0.86	-0.32	-	-	-	-0.94	-0.99	-
WF7	-0.68	0.65	-	0.61	0.91	0.86	0.98	-	0.74	-0.38	-	-	-	-0.99	-0.88	-
WF8	-0.82	0.65	-	0.34	0.90	0.80	0.86	0.74	-	-0.63	-	-	-	-0.77	-0.84	-
WF9	0.85	-0.89	-	-0.61	-0.40	-0.17	-0.32	-0.38	-0.63	-	-	-	-	0.44	0.25	-
WF13	0.72	-0.68	-	-0.66	-0.92	-0.86	-0.94	-0.99	-0.77	0.47	-	-	-	-	0.88	-
WF14	0.63	-0.38	-	-0.41	-0.99	-0.99	-0.99	-0.88	-0.84	0.25	-	-	-	0.88	-	-

[a]Coefficients are significant at P= 0.05.
[b]Meteorological factors (WF) have different durations as presented in Table III.3d. WF1= TPREC; WF2= CDWOP; WF3= DR84; WF4= MMAX; WF5= MMIN; WF6= MAVE; WF7= DOPT; WF8= CDOPT; WF9= DG25C; WF10= CDRH80; WF11= DRH80; WF12= MRH; WF13= MWS; WF14= DWS35; WF15= MSR. Descriptions of meteorological factors are presented in Table III.1.

Table III.3a. Durations of meteorological factors in days after sowing having highest correlation with rice blast parameters on IR50 at the IRRI blast nursery, Philippines as found by WINDOW PANE program.

Meteorological factor[b]	Disease parameters (DP)[a]	
	FDLA	PBS
Rainfall		
PFREQ	24	-
CDWP	24	-
CDWOP	26	-
Temperature		
DG25C	37	50
Relative humidity		
DRH80	-	69
CDRH80	-	69
MRH	-	74
Wind speed		
MWS	27	-

[a]FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.
[b]Descriptions of meteorological factors are presented in Table III.1.

Table III.3b. Durations of meteorological factors in days after sowing having highest correlation with rice blast parameters on C22 at Gunung Medan and Sitiung, West Sumatra, Indonesia as found by WINDOW PANE program.

Meteorological factor[b]	Disease parameters[a]		
	Gunung Medan	Sitiung	
	PBIn	FLBIn	PBIn
Rainfall			
TPREC	-	20	68
PFREQ	70	-	20
CDWP	61	14	31
CDWOP	70	-	34
Temperature			
MMAX	51	-	19
MMIN	25	-	19
MAVE	53	-	19
DOPT	34	41	41
CDOPT	33	-	40
DG25C	-	-	30
Relative humidity			
DRH80	22	-	20
CDRH80	21	-	-
MRH	35	-	-
Solar radiation			
MSR	30	23	-

[a]PBIn= Panicle blast index; FLBIn= final leaf blast index.
[b]Descriptions of meteorological factors are presented in Table III.1.

Table III.3c. Durations of meteorological factors in days after transplanting having highest correlation with rice blast parameters on Jin heung cultivar at Icheon, South Korea as found by WINDOW PANE program.

Meteorological factor[b]	Disease parameters (DP)[a]				
	ML1	ML2	FL1	FL2	PBI2
Rainfall					
TPREC	30	-	40	-	43
PFREQ	-	-	-	35	
CDWP	-	-	-	30	-
CDWOP	-	-	-	30	-
DR84	-	-	-	-	-
Relative humidity					
DRH80	29	5	40	23	45
CDRH80	28	5	28	23	43
MRH	-	-	-	30	-
Temperature					
DOPT	-	4	-	-	-
MMAX	-	-	-	39	-
DG25C	-	-	-	23	-
Sunshine duration					
MSD	28	-	32	-	-
Solar radiation					
MSR	28	-	-	-	-

[a]ML= Maximum lesion number; FL= final lesion number; PBI= percent panicle blast incidence. A "1" following DP would mean 110 kgN/ha treatment; "2" means 220 kgN/ha treatment. PBI1 was not included because only one meteorological factor was found correlated with panicle blast.
[b]Descriptions of meteorological factors are presented in Table III.1.

Table III.3d. Durations of meteorological factors in days after sowing having highest correlation with rice blast parameters on IR50 and C22 cultivars at Cavinti, Laguna, Philippines as found by WINDOW PANE program.

Meteorological factor[b]	Disease parameters (DP)[a]					
	IR50			C22		
	MDLA	FDLA	PBS	MDLA	FDLA	PBS
Rainfall						
TPREC	33	17	37	16	-	85
CDWOP	-	-	47	-	-	-
DR84	27	27	-	27	-	52
Temperature						
MMAX	34	33	-	34	40	44
MMIN	29	26	-	31	-	76
MAVE	34	34	-	33	40	44
DOPT	29	26	72	26	-	65
CDOPT	-	-	-	23	-	64
DG25C	-	34	-	-	36	59
Relative humidity						
CDRH80	-	-	-	-	-	-
DRH80	-	22	53	-	-	-
MRH	-	36	49	-	-	-
Wind speed						
MWS	36	35	-	-	19	48
DWS35	36	36	-	36	38	54
Solar radiation						
MSR	-	-	56	30	18	-

[a]MDLA= Percent maximum diseased leaf area; FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.
[b]Descriptions of meteorological factors are presented in Table III.1.

Table III.4a. Path coefficients of the direct (Py) and total effects of meteorological factors at Icheon, South Korea found highly correlated with rice blast parameters on Jin heung cultivar by WINDOW PANE program.[a]

Meteorological factors[b] (WF)	Disease parameters[c]				
	ML1	ML2	FL1	FL2	PB2
Rainfall					
TPREC	+0.37(+0.58)	-	+0.41(+0.68)	-	-0.39(-0.70)
PFREQ	-	-	-	+0.37(+0.58)	-
CDWP	-	-	-	+0.43(+0.59)	-
CDWOP	-	-	-	-0.35(-0.57)	-
Relative humidity					
DRH80	+0.45(+0.62)	+0.44(+0.62)	+0.53(+0.81)	+0.56(+0.64)	-0.11(-0.76)
CDRH80	+0.38(+0.61)	+0.59(+0.71)	+0.67(+0.84)	+0.43(+0.63)	-0.86(-0.79)
MRH	-	-	-	+0.28(+0.57)	-
Temperature					
DOPT	-	-0.42(-0.57)	-	-	-
MMAX	-	-	-	-0.31(-0.53)	-
DG25C	-	-	-	-0.37(-0.58)	-
Sunshine duration					
MSD	-0.94(-0.67)	-	-0.25(-0.56)	-	-
Solar radiation					
MSR	+0.12(-0.56)	-	-	-	-

Table III.4a. Footnotes

[a]Number in parenthesis is the total effect or correlation coefficient of a meteorological factor with a disease parameter.
[b]Meteorological factors for each disease parameter have durations as presented in Table III.3c. Descriptions of meteorological factors are presented in Table III.1.
[c]Disease parameters (DP) of rice blast. ML= Maximum lesion number; FL= final lesion number; PBI= percent panicle blast incidence. A "1" following DP would mean 110 kgN/ha treatment, whereas, "2" means 220 kgN/ha treatment. Panicle blast incidence at 110 kgN/ha was not included because only one factor was found correlated with this parameter.

Table III.4b. Path coefficients of the direct (Py) and total effects of meteorological factors at Cavinti, Laguna, Philippines found highly correlated with rice blast parameters on IR50 and C22 cultivars by WINDOW PANE program.[a]

Meteorological factor[c] (WF)	Disease parameters[b]					
	IR50			C22		
	MDLA	FDLA	PBS	MDLA	FDLA	PBS
Rainfall						
TPREC	+0.43 (+0.71)	+0.60 (+0.70)	+0.04 (-0.53)	+0.75 (+0.77)	-	-0.62 (-0.83)
CDWOP	-	-	+1.07 (+0.59)	-	-	-
DR84	+0.23 (+0.65)	+0.50 (+0.71)	-	+0.50 (+0.75)	-	-0.42 (-0.69)
Temperature						
MMAX	-0.01 (+0.72)	+0.15 (+0.56)	-	+0.13 (+0.67)	-0.22 (-0.58)	-1.60 (-0.73)
MMIN	+0.85 (+0.80)	+0.78 (+0.76)	-	+0.49 (+0.72)	-	+1.48 (-0.57)
MAVE	+0.19 (+0.76)	+0.45 (+0.68)	-	+0.46 (+0.70)	+0.25 (-0.57)	-0.38 (-0.68)
DOPT	-0.02 (-0.64)	-0.33 (-0.57)	-0.22 (-0.58)	-0.32 (-0.73)	-	+0.35 (-0.68)
CDOPT	-	-	-	-0.32 (-0.73)	-	-0.74 (-0.82)
DG25C	-	+0.02 (+0.54)	-	-	-0.73 (-0.75)	+0.66 (+0.85)
Relative humidity						
CDRH80	-	-	-	-	-	-
DRH80	-	+0.10 (+0.57)	+0.24 (-0.57)	-	-	-
MRH	-	+0.38 (+0.55)	-0.36 (-0.58)	-	-	-
Wind speed						
MWS	-0.64 (-0.79)	-0.72 (-0.74)	-	-	+0.65 (+0.75)	+1.25 (+0.72)
DWS35	-0.41 (+0.75)	-0.49 (-0.68)	-	-0.57 (-0.78)	+0.73 (+0.75)	+0.47 (+0.63)
Solar radiation						
MSR	-	-	+0.41 (+0.58)	+0.53 (+0.76)	-0.13 (-0.69)	-

Table III.4b. Footnotes

[a]Number in parenthesis is the total effect or correlation coefficient of a meteorological factor with a disease parameter.
[b]MDLA= Percent maximum diseased leaf area; FDLA= percent final diseased leaf area; PBS= percent panicle blast severity;
[c]Meteorological factors for each disease parameter have different durations as presented in Table III.3d. Descriptions of meteorological factors are presented in Table III.1.

Table III.4c. Path coefficients of the direct (Py) and total effects of meteorological factors at the IRRI blast nursery, Philippines having highest correlation with rice blast parameters on IR50 cultivar as found by WINDOW PANE program.[a]

Meteorological factor[c]	Disease parameters[b]	
	FDLA	PBS
Rainfall		
PFREQ	+0.42(+0.53)	-
CDWP	+0.19(+0.41)	-
CDWOP	-0.36(-0.51)	-
Temperature		
DG25C	+0.49(+0.58)	+0.42(+0.52)
Relative humidity		
DRH80	-	-0.02(+0.46)
CDRH80	-	+0.74(+0.50)
MRH	-	+0.07(+0.40)
Wind speed		
MWS	-0.25(-0.41)	-

[a]Number in parenthesis is the total effect or correlation coefficient of a meteorological factor with a disease parameter.
[b]FDLA= Percent final diseased leaf area; PBS= percent panicle blast severity.
[c]Meteorological factors for each disease parameter have different durations as presented in Table III.3a. Descriptions of meteorological factors are presented in Table III.1.

Table III.4d. Path coefficients of the direct (Py) and total effects of meteorological factors at Gunung Medan and Sitiung, West Sumatra, Indonesia having highest correlation with rice blast parameters on C22 cultivar as found by WINDOW PANE program.[a]

Meteorological factor[c]	Disease parameters[b]		
	Gunung Medan	Sitiung	
	PBIn	FLBIn	PBIn
Rainfall			
TPREC	-	-0.43(-0.65)	-0.41(-0.73)
PFREQ	+0.84(+0.93)	-	-0.32(-0.71)
CDWP	+0.78(+0.93)	-0.34(-0.62)	-0.32(-0.70)
CDWOP	-0.47(-0.83)	-	+0.15(+0.68)
Temperature			
MMAX	+0.55(+0.82)	-	-0.48(-0.81)
MMIN	-0.14(-0.68)	-	-0.31(-0.65)
MAVE	+0.32(+0.74)	-	-0.54(-0.76)
DOPT	+0.27(+0.73)	-0.48(-0.68)	-0.71(-0.77)
CDOPT	+0.46(+0.74)	-	-0.30(-0.76)
DG25C	-	-	-0.68(-0.80)
Relative humidity			
DRH80	+0.64(+0.81)	-	+0.33(+0.66)
CDRH80	+0.32(+0.79)	-	-
MRH	+0.28(+0.71)	-	-
Solar radiation			
MSR	-0.38(-0.73)	+0.47(+0.67)	-

[a]Number in parenthesis is the total effect or correlation coefficient of meteorological factor with disease parameter.
[b]PBIn= Panicle blast index; FLBIn= final leaf blast index.
[c]Meteorological factors for each disease parameter have different durations as presented in Table III.3b. Descriptions of meteorological factors are presented in Table III.1.

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CHAPTER IV
USE OF MULTIVARIATE STATISTICAL PROCEDURES TO DETERMINE THE EFFECT OF SOWING TIME ON PRONENESS OF TROPICAL RICE TO BLAST

ABSTRACT

Patterns in the relationship between blast outbreak and time of sowing at three tropical sites in Asia were analyzed using multivariate statistical procedures. A matrix of predicted leaf and panicle blast (columns) by 24 hypothetical sowing times (or sowing months) (rows) was constructed at each site to determine such patterns. Sowing months were grouped according to blast outbreaks for various cultivars and sites using cluster analysis. Three groups of sowing months were identified at each site. Ordination by principal component analysis revealed that for IR50 cultivar, most sowing months in Groups II and III at Cavinti, Philippines were prone to leaf and panicle blast, while months in Group I were prone only to panicle blast. With C22 cultivar, plants sown in Group III months would likely have leaf blast, while panicle blast would be likely with sowing during months in Group I. At the IRRI blast nursery, Philippines, leaf and panicle infections on IR50 would be probable in months in Groups I and II. This trend was also observed at Sitiung, Indonesia with C22, but blast severity was low when sown in Group II months.

INTRODUCTION

Blast, a disease in rice caused by *Pyricularia grisea* (Cooke) Sacc. (Rossman et al., 1990) is a perennial problem in tropical rice ecosystems because of the frequent occurrence of widespread epidemics that cause tremendous losses in yield (James et al., 1990). The disease is most severe at the seedling stage of a susceptible rice cultivar (Ou, 1985), but also persists to maximum tillering under optimum environmental conditions (Ou, 1985; Torres, 1986). Although there is no direct relationship between leaf and panicle blasts (Teng et al., 1991), lesions on leaves may provide inoculum for neck and panicle infections (Ishiguro and Hashimoto, 1988, 1991).

Rice blast is potentially devastating in both lowland and upland rice production areas whenever susceptible cultivars are grown. Strategies to manage the disease have been the focus of extensive research by national and international research programs at blast prone sites in Asia (Teng et al., 1991). Use of resistant cultivars has been advocated in developing countries because it is economically feasible, environmentally sound, and can be easily adopted by farmers and disseminated to different production areas (Bonman et al., 1992; Teng, 1993). Biological control of blast is promising but not yet fully applied in most production situations (Gnanamanickam and Mew, 1990). Chemical control is common in temperate areas (Teng, 1993).

Knowledge of the underlying pathosystem is important to formulate sound management decisions. Disease outbreaks result from the interactions of the components of the pathosystem which are in turn driven by optimum factors in the environment, host susceptibility, and pathogen virulence (Agrios, 1988). Temporal and spatial disease progression tend to depend on these driving factors. Adjusting or manipulating these factors may either accelerate or slow disease progression through time, or may either spread out the disease across fields or have it concentrated on certain areas only. Empirical knowledge about the relationship of weather to disease patterns is one of the bases for managing blast.

There are several statistical approaches to exploit the relationship between weather and disease. Regression and correlation analyses are useful in determining linear relationships. Non-linearity can often be explained with the use of non-linear regression procedures. Use of path coefficient analysis offers better estimation of relationships that exist between weather and disease than correlation analysis (Bowers and Mitchell, 1988; Bowers et al., 1990). Multivariate procedures have not been commonly used to investigate the effect of environment on epidemic development. Often used in yield loss studies (Campbell and Madden, 1990), they have also been shown useful for epidemiological studies, such as relating disease with cultural practices (Savary et al., 1993) and predicting disease onset as related to prevailing weather conditions (personal communication, Harald Scherm, University of California at Davis).

Classification and ordination are two of the most important techniques in multivariate analysis. Classification is concerned with separating distinct sets of observations and with allocating new observations to previously defined groups (Johnson and Wichern, 1992). Cluster and discriminant analyses are two techniques commonly used in classification. Ordination, on the other hand, attempts to find major axes of variation among observations inorder to reduce the many dimensions of a data set to a very few, with minimum loss of information (Anderson, 1971; Beals, 1984). Principal component analysis is the most common technique of ordination, although several other techniques are available in ecological studies (Anderson, 1971).

In this chapter, cluster, discriminant, and principal component analyses are used to identify proneness of crop-growing months for two sites in the Philippines and one site in Indonesia. Linear discriminant functions were also generated to match new sowing months to the proneness groups obtained through cluster analysis. These statistical procedures will help predict the potential of blast epidemics. Such predictions allow early, cost-saving management decisions. These methods may also help identify the appropriate time and place for establishing blast-related research sites to maximize exposure of plants to the disease.

MATERIALS AND METHODS

General procedure. The flow diagram of the procedure used in this study is shown in Fig. IV.1. This procedure was followed at every site and for every cultivar at the same site. Initially, disease and meteorological databases were secured for Cavinti and the International Rice Research Institute (IRRI) blast nursery in the Philippines, and Sitiung in Indonesia. The disease databases were obtained from field experiments using cultivars IR50 (at Cavinti and IRRI) and C22 (at Cavinti and Sitiung). The meteorological databases contained daily values of weather variables recorded for several years. From disease and weather databases, cultivar-specific predictive models for rice blast were developed through regression analysis. At the same time, a weather database was simulated for disease predictions and for use in multivariate analysis. Using weather factors from a simulated database as predictors in the models, final diseased leaf area (DLA) and panicle blast severity were predicted for each cultivar for 24 hypothetical sowing dates. Maximum DLA was also predicted at Cavinti. The predicted disease values served as attributes in the main data matrix for multivariate analysis. The secondary data matrix had weather factors as attributes with durations from sowing to disease onset and from sowing to flowering stage of the cultivar. Cluster analysis was applied to the main matrix to identify blast proneness groups. Principal component analysis was applied to both the main and secondary matrices to characterize these groups. Discriminant analysis was then used to develop discriminant functions to allow new sowing dates to be allocated to the previously defined groups. These methods are described in detail below.

Models of blast parameters. Regression models of rice blast parameters were generated for the three tropical sites using meteorological factors found correlated with disease by WINDOW PANE program (Calvero and Coakley, 1993 unpublished; Coakley et al., 1982, 1985, 1988a, 1988b) as predictors. Models with high adjusted coefficient of determination (R^2), relatively low Allen's Predicted Error Sum of Squares (PRESS) values (Myers, 1990; Neter et al., 1989), a coefficient of variation (CV) below 25 % (Myers, 1990), near unity probability less than W of the distribution of studentized residuals ($P< W$) (Neter et al., 1989), and high percentage accuracy (ACC) of prediction were chosen as best models predicting disease (Tables IV.1). In particular, ACC was estimated based on a contingency quadrant (Chapter II: Fig. II.3) that relates actual disease value with predicted value. Using specified cutoff points (Chapter II: Table II.3), ACC was calculated using Eqn. II.1 (Chapter II) as described by Coakley et al. (1988a, 1988b).

Generation of meteorological data used in the analysis. Historical weather databases containing daily values of maximum, minimum, and mean temperature (C), rainfall (mm/day), average relative humidity (%), wind speed (m/s), and solar radiation (MJ/m^2) were secured at each site from the IRRI Climate Unit. Wind speed values were not available at Sitiung. Two (1985-1986), seven (1987-1993), and eight (1985-1992) years of data were available at Sitiung, Cavinti, and IRRI, respectively.

To predict the disease at various sowing times, three full years of weather extracted from historical weather databases were required at each site. The second year being the best representation of the long-term weather pattern at the site, the first and third year took care of weather factors (predictors) which had durations starting or terminating before or beyond the target planting dates, respectively. For example, a factor with duration starting 20 days before sowing used as predictor of disease on cultivars planted on January 1 would require daily values in December of the previous year. Likewise, a factor with duration terminating 70 days after sowing used as predictor of disease on cultivars planted December 15 would require daily values in January and February of the next year.

Extraction of a three full year weather from a historical database was done using a weather simulation program called SIMMETEO (Geng et al., 1988). Getting the daily averages of weather variables across several years could have been done to assemble a new database that was used in predicting blast. However, it was difficult to get averages from non-leap and leap years (especially after the end of February) due to the difference in the number of days. For example, it is not proper to assign the average of maximum temperature (TMAX) recorded on February 29, 1988 (leap year) and March 1, 1989 (non-leap year) to March 1's TMAX in the new database. In addition, only one full-year data could be generated from averaging the variables across several years. Simulation was used to minimize these problems while accounting for the variations and statistical properties of variables in the actual (historical) weather data.

A 12-month mean values of fraction of wet days (ratio of number of wet days and number of days in a month), ratio of total rainfall and number of wet days, maximum and minimum temperatures, solar radiation or sunshine duration, vapor pressure, and wind speed served as input data to SIMMETEO. A 100-year simulated weather data set was then generated for each site. Treating the input values as the observed group and simulated monthly values as the estimated group, canonical discriminant analysis was employed to search for the most typical simulated year, based on likelihood ratios and probability values for F-ratios near unity. The years immediately before and after the best simulated year completed the weather database.

Data matrix. The data set for multivariate analysis at each site was composed of main and secondary matrices. The main matrices for all the sites had 24 sowing months (rows) by two blast parameters (columns), except for Cavinti, which had a 24 x 3 matrix. The secondary matrices had 24 sowing months (rows) by 34 weather factors (columns) at Cavinti, 24 x 32 at the IRRI blast nursery, and 24 x 30 at Sitiung. Since Cavinti had two cultivars, separate main and secondary matrices for each cultivar were used in the analysis. In general, the main matrix was used in classification and ordination of crop-growing months, and the secondary matrix for investigating the influence of environment on these months.

Twenty four hypothetical sowing months beginning on January 1 and ending on December 15 with 15-day interval between months served as samples (rows) for analysis. Blast parameters such as maximum and final diseased leaf area (DLA) and panicle blast severity (PBS), final DLA and PBS, and leaf and panicle blast indices estimated using best models (Table IV.1) at Cavinti, IRRI blast nursery, and Sitiung, respectively, served as attributes in the main data matrices. Weather factors with durations from sowing to disease onset and from sowing to flowering stage of the crop served as attributes in the secondary data matrices.

Transformation was applied to the values in the main matrix because of three reasons: 1) to produce equal weightings of the attributes in the analysis; 2) to reduce occurrence of outlying samples; and 3) to produce multivariate normal distribution among attributes. Following conversion of percentage values of severity to proportions, attributewise relativization by norm (Greig-Smith, 1983) was made on the IR50 data set at Cavinti. Relativization by norm was estimated with p= 2 (Greig-Smith, 1983), and is shown as

$$b = \frac{x_{ij}}{(\Sigma\ x_j^p)^{1/p}}$$

where b is the transformed value and x_{ij} is the value in the matrix at ith row and jth column. With C22 however, this relativization method together with arc-sine square root were employed to improve normality. This procedure was also applied to the IRRI blast nursery data set. No adjustments were made to the data at Sitiung as the range of values was narrow.

Multivariate analysis. Hierarchical and agglomerative clustering via Ward's method (Wishart, 1969), which is available in the PC-ORD system (McCune, 1993), was employed to classify sowing times into distinct blast-proneness groups (BPG). Relative Euclidean was chosen as distance measure based on considerable reduction in percent chaining of cluster dendrograms. Separation of BPGs was done by slicing cluster dendrograms at specific distance measures. Significance of group differences was tested using the discriminant analysis procedure (PROC DISCRIM) in the Statistical Analysis System (SAS) package (SAS Institute Inc., 1988).

Principal component analysis (PCA) with variance-covariance as the resemblance measure was used to ordinate sowing months with blast parameters as attributes. This ordination method was used since the data matrices appeared homogenous and roughly had multivariate normal distribution of values. Pearson correlation analysis of attributes in main and secondary matrices with principal component axis scores was done to explore the relationship of the environment to the ordination of sowing months. The relationship was further investigated by stepwise discriminant analysis to identify the most important meteorological factors related to BPGs. Discriminant analysis generated predictive functions that can be used to classify new sowing months into any of the proneness groups.

RESULTS

Cluster analysis. Three groups of months with varying degree of proneness to leaf and panicle blast outbreaks were determined from among hypothetical sowing dates. Fewer or more groups could have been distinguished, but the three group level in the cluster analysis provided distinction of dry and wet months and the transition from season to season. No misclassified months were obtained from the groups identified. This supported the choice for the three group level.

Grouping of months at Cavinti differed between IR50 and C22 cultivars. Months in blast proneness group (BPG) III of C22 cultivar mostly fell in group II of IR50 and months belonging to group II of C22 were members of either groups II or III of IR50 (Table IV.2). Similarly, blast-proneness groups from Cavinti and IRRI with IR50 cultivar showed entirely different membership composition. The majority of sowing months at IRRI fell under group I. These same months were categorized under group II at Cavinti (Table IV.2). At Sitiung, the majority of months fall under group III followed by group II (Table IV.2).

Principal component analysis. Distinctness of groups was evaluated by examining their degree of variation in the first two principal components. At Cavinti, 90 % of the total variation in the data set was explained by the first principal component for IR50, whereas, two components were needed to explain this degree of variation for C22 (Fig. IV.2a). A more random distribution of months was discernible in IR50 ordination, while a clumped pattern was observed in C22 (Fig. IV.2a).

Amount of variation explained by principal component 1 at IRRI was obviously larger than at Cavinti because only two blast parameter attributes were used in the ordination analysis at IRRI. The first principal component, respectively, explained 94 % and 85 % of the total variation in the data set at IRRI and Sitiung (Fig. IV.2b). Sowing months at IRRI were more or less concentrated along the periphery of ordination, while at Sitiung, a slightly random distribution of months was discernible (Fig. IV.2b).

Correlating ordination scores with disease parameter attributes on IR50 at Cavinti showed principal component 1 explaining variations among sowing months due to differences in maximum and final diseased leaf area (DLA) (Table IV.3a). The relationship was stronger with final DLA (correlation coefficient, r= -0.99) than with maximum DLA (r= -0.89) (Table IV.3a). Variation explained by principal component 2 was attributed to differences in panicle blast severity (r= -0.90). On the other hand, with C22 at Cavinti, the first principal component explained variations due to final DLA alone (r= -0.98). Variations explained by the second component were due to differences in both maximum DLA and panicle blast severity on C22 (Table IV.3a).

Meteorological factors at Cavinti with durations from sowing to disease onset (t_0) or from sowing to crop flowering stage (t_f) showed higher correlation with ordination scores on IR50 than on C22 (Table IV.3a). In ordinating months using IR50, the number of days with wind speed above 3.4 m/s (DWS35) occurring at t_0 and consecutive days with rainfall (CDWP) occurring at t_f had the highest correlation with first (r= 0.85) and second (r= 0.88) principal components, respectively (Table IV.3a). In ordinating months using C22, total precipitation (TPREC) occurring at t_0 and both consecutive days with mean temperature of 20-27 C (CDOPT) occurring at t_f and DWS35 occurring at t_0 gave the highest correlations with the first (r= -0.68) and second (r= -0.57) principal components, respectively (Table IV.3a).

At the IRRI blast nursery, only the first component was needed to explain majority of the variations in the data set. These variations were largely due to differences in final DLA and panicle blast severity (Table IV.3b). The number of days with maximum temperature over 25 C (DG25C) and average relative humidity (MRH) at the nursery occurring at t_0 and t_f, respectively, gave the highest correlation (r= 0.71) with principal component 1 (Table IV.3b).

At Sitiung, final leaf blast index had high correlation with principal component 2 (r= 0.95), while panicle blast had high correlation (r= 0.99) with principal component 1 (Table IV.3c). A temperature factor, DG25C, occurring at t_0

gave strongest correlation with principal component 1 (r= -0.90). A rainfall factor, TPREC, occurring at t_0 had the same degree of relationship with the second component (Table IV.3c).

Discriminant analysis. Meteorological factors that had high correlation with principal component axes were further investigated with stepwise discriminant analysis. These factors were included in discriminant functions (Table IV.4) that can be used to predict proneness groups for future sowing months. The expected actual error rate (E(AER)) of misclassification was low in most of the functions generated (Table IV.4). However, one function that allocated sowing months to group III with proneness to panicle blast on C22 at Cavinti had high misclassification rate (E(AER)= 50%) (Table IV.4). Functions that allocated months into panicle blast proneness group I at Cavinti with C22 and at IRRI with IR50 had no misclassified observations (E(AER)= 0%) (Table IV.4). Similarly, functions that allocated months to panicle and leaf blasts proneness group III at Sitiung had zero rates of misclassification (Table IV.4).

DISCUSSION

In tropical locations, blast epidemics can occur anytime during the year due to the frequency of planting, consistency in using a single rice genotype, and inflexibility of cultural practices employed in production (Teng et al., 1993). It has been noted that although the severity of blast is relatively independent of the crop intensification process (Teng, 1993), patterns of weather conditions that exist in certain tropical locations have elevated the occurrence of the disease to damaging levels.

In this study, three groups of sowing months were generated. Each group had distinct characteristics to measure the degree of proneness of cultivars to leaf and panicle blast when sown during these dates. It was shown that the chance of having an outbreak is influenced by the weather conditions which differ from site to site and from cultivar to cultivar at a particular site.

At Cavinti, if C22 is sown during June 15-August 1 (group III), panicle blast infection is less likely to occur (Figs IV.2a and IV.3a). Sowing IR50 during these months, however, would produce severe leaf and panicle infections (Figs. IV.2a and IV.3b). If both cultivars are sown in months belonging to group I (January 1-May 1 for C22 and January 1-May 15, August 15 for IR50), the chance of having panicle blast is high, but there is less probability of leaf blast. In general, there is lesser chance for IR50 to escape blast infections at Cavinti than C22 because upland cultivation of the former cultivar predisposes it to infection by *P. grisea*. The cultivars IR50 and C22 are both susceptible to blast, but the former is not bred for upland conditions. Temperature appears directly linked to increased predisposition of IR50 at Cavinti. Higher correlation of temperature factors to ordination scores of IR50 than of C22 suggest this (Table IV.3a). Rotem (1978) showed that a temperature increase may trigger decline of host resistance to pathogen attack.

Wind speed at Cavinti produced positive correlation with principal component 1 for IR50 and C22 (Table IV.3a). At the same time, negative correlations were given by maximum and final DLA with principal component 1 for both cultivars (Table IV.3a). Such a relationship suggest that increasing wind speeds reduce the possibility of leaf infection. The effect of wind beyond 3.4 m/s is related to the violent liberation of spores from leaves and to long-distance dissemination. Suzuki (1975) reported that in areas or in years with strong winds, less infection is observed because disease is distributed uniformly in the field and few spores are retained within crop canopies. Furthermore, strong wind may increase plant resistance because of possible silification of host tissues (Kumagawa et al., 1957). However, strong wind (wind above 4-5 m/s) also tend to injure plants and thus, may facilitate pathogen penetration of host tissues (Sakamoto, 1940) inducing more disease.

At Cavinti, total precipitation, frequent rainfall, and consecutive days with rain occurring from sowing to flowering stage of the crop showed high positive correlations with principal component axes. Panicle blast had negative correlation with these axes (Table IV.3a). This suggests that at Cavinti, rainfall factors are directly involved in limiting the amount of inoculum during the crop flowering stage for panicle infection by washing-off spores from potential inoculum sources such as infected leaves. Once spores are washed-off, inoculum is reduced resulting in a decrease in the occurrence of panicle infection (Suzuki, 1975). However, rainfall factors, especially those with durations from sowing to onset also favored leaf infection (Table IV.3a). This relationship was shown with leaf blast parameters and rainfall factors both having negative correlations with principal component 1 in both cultivars. Although rainfall may wash-off newly produced spores from leaves, it also provides moisture for other spores previously attached on the leaves. This free moisture is required by *P. grisea* spores already deposited on host tissues for infection to occur (Gunther, 1986).

In characterizing the groups generated for Cavinti, months under group I are prone to panicle blast (Figs. IV.3a-b) due to more days with wind beyond 3.4 m/s and less rain. Months under group II are prone either to high maximum leaf blast severity (both IR50 and C22) (Figs. IV.3a-b) or high final leaf blast severity (IR50 only) (Fig. IV.3b) due to low wind speeds or frequent rainfall. Months under group III are prone to both high maximum and final leaf blast severity (IR50 and C22) (Figs. IV.3a-b) due to low wind speed but with considerably higher temperatures. The proneness of sowing months to blast using IR50 and C22 cultivars is presented by the size of the diamonds in Figs. IV.3a-b; where big diamonds represent high degree of proneness.

At IRRI, sowing months falling within groups I and II (Table IV.2) appeared to have similar proneness to leaf and panicle blast outbreaks (Figs. IV.2b and IV.3c). However, IR50 could have lesser infection all throughout its growth if planted in months belonging to group III than in months under either groups I or II. It was observed that the likelihood of getting blast infection in months falling under the first two groups was related to the number of days having maximum temperature above 25 C (DG25C) and average relative humidity (MRH) occurring from sowing to flowering. The positive relationship of these factors with the first principal component (Table IV.3b) showed that increase in disease is due to more days with temperature above 25 C and high humidity. Since average temperature at IRRI is commonly over 25 C (Fig. IV.4), it is unlikely that the temperature effect at this site would be greater than the humidity effect. Studies have shown that optimum blast development requires high humidity. El Refaei (1977) demonstrated that stages in the pathogen monocycle from spore liberation to sporulation are either directly or indirectly affected by humidity. In panicle blast development, high humidity prolongs the wetness period in spikelets which triggers spore germination and aids in the infection process (Ishiguro and Hashimoto, 1991). In describing groupings at the IRRI blast nursery, months under groups I and II have the same level of proneness to both leaf and panicle blast (Fig. IV.3c) mainly because of high humidity conditions. Months in group III are not prone to both leaf and panicle blast (Fig. IV.3c) outbreaks because of lower humidity.

At Sitiung, months in group II showed a high degree of proneness to both leaf and panicle blast diseases (Figs. IV.2b and IV.3d). Some months in group I also gave higher possibility of getting both blast outbreaks than months in other groups. Generally, months in the third group are more prone to leaf blast than to panicle blast (Figs. IV.2b and IV.3d). Proneness to leaf blast appeared to be influenced by low amount of rainfall occurring from sowing to disease onset at this site. This effect supports previous blast epidemiology studies since it has been known that low rainfall amount prevents washing off of spores from leaves (Gunther, 1986; Kato, 1974; Suzuki, 1975). Such an occurrence allows more propagules to be retained within the canopy to increase autoinfection among tissues, and to provide free moisture for infection. Proneness to panicle blast on the other hand, is largely affected by temperature factors. The increased number of days with maximum temperature beyond 25 C (DG25C) from sowing to disease onset reduces panicle infection probably because of its effect on leaf blast directly rather than on panicle blast. Since DG25C had a duration occurring before the crop flowering stage, the possible consequence of this factor on panicle blast is primarily due to its effect on the sporulation potential of leaf lesions. High temperature reduces sporulation potential of lesions (El Refaei, 1977; Kato and Kozaka, 1974). Such an occurrence causes a reduction in inoculum to initiate panicle infection, unsuccessful secondary leaf infections (El Refaei, 1977; Kato, 1974), and desiccation of air-borne spores (Rotem, 1978). The latter decreases the proportion of spores surviving to infect the panicles.

Differences in group membership among sites based on blast proneness are extremely difficult to identify by investigating long-term weather patterns alone. As shown in Fig. IV.4, actual weather trends at the three sites show similarity. Based on discriminant procedures, various meteorological factors influenced the classification of sowing months into their proneness to blast outbreak. It is important to note that discriminant functions generated here are cultivar- and location-specific. However, verifying the ability of these mathematical functions to predict outbreaks in other areas using different sets of cultivars is a next step. A generalized method can potentially be used to categorize tropical blast hot-spot areas into groups based on the physical environment. At the same time, it is possible to categorize different rice cultivars into susceptibility groups based on their reactions to blast. In the present study, predictive models from regression or discriminant analyses have been generated using sites or cultivars representative of their respective groups. A generalized method can result in the use of mathematical models to predict disease severity or blast outbreaks on cultivars with different genotypic backgrounds and at different locations.

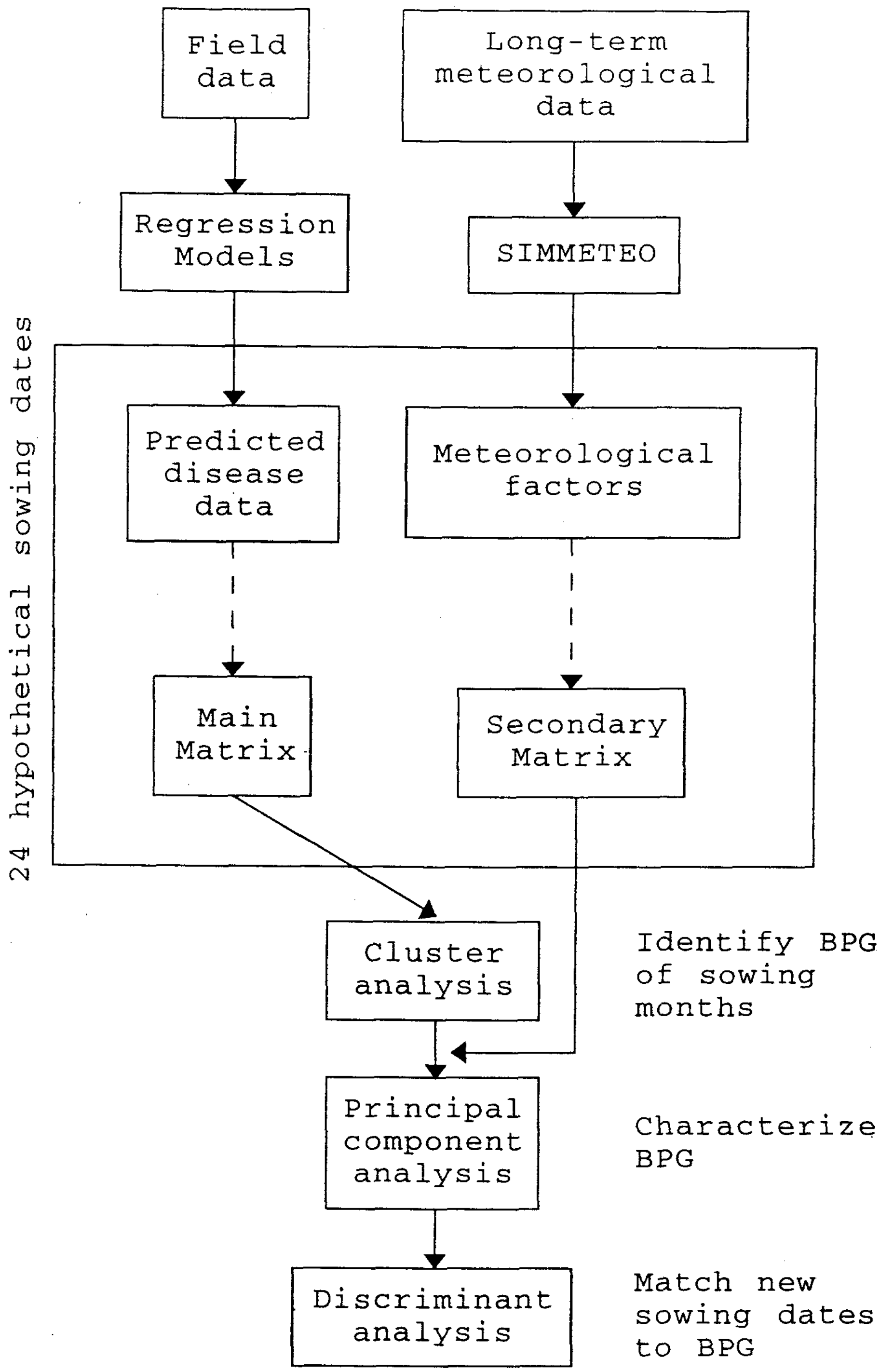


Fig. IV.1. Flow diagram of the procedure to determine the effect of sowing dates on proneness of tropical rice to blast. BPG= Blast proneness group.

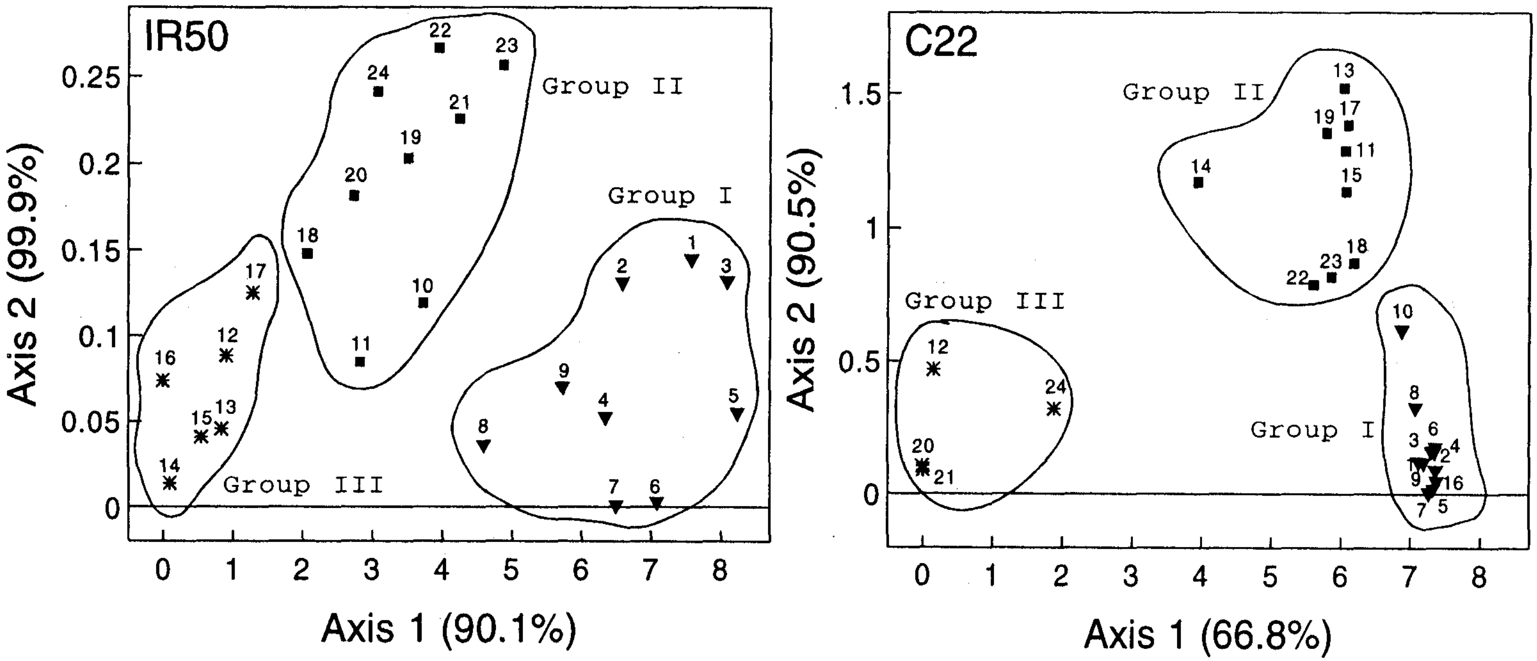


Fig. IV.2a. Ordination of 24 hypothetical sowing months at Cavinti, Philippines using blast parameters on IR50 and C22 cultivars as attributes for principal component analysis. Numbers in parentheses are the percent cumulative variances of principal component axes. Numbers beside the markers are the sowing dates, i.e. 1= January 1; 2= January 15; 3= February 1; and so on. Markers represent blast proneness groups identified by cluster analysis, i.e. Group I (▼); Group II (■); Group III (*).

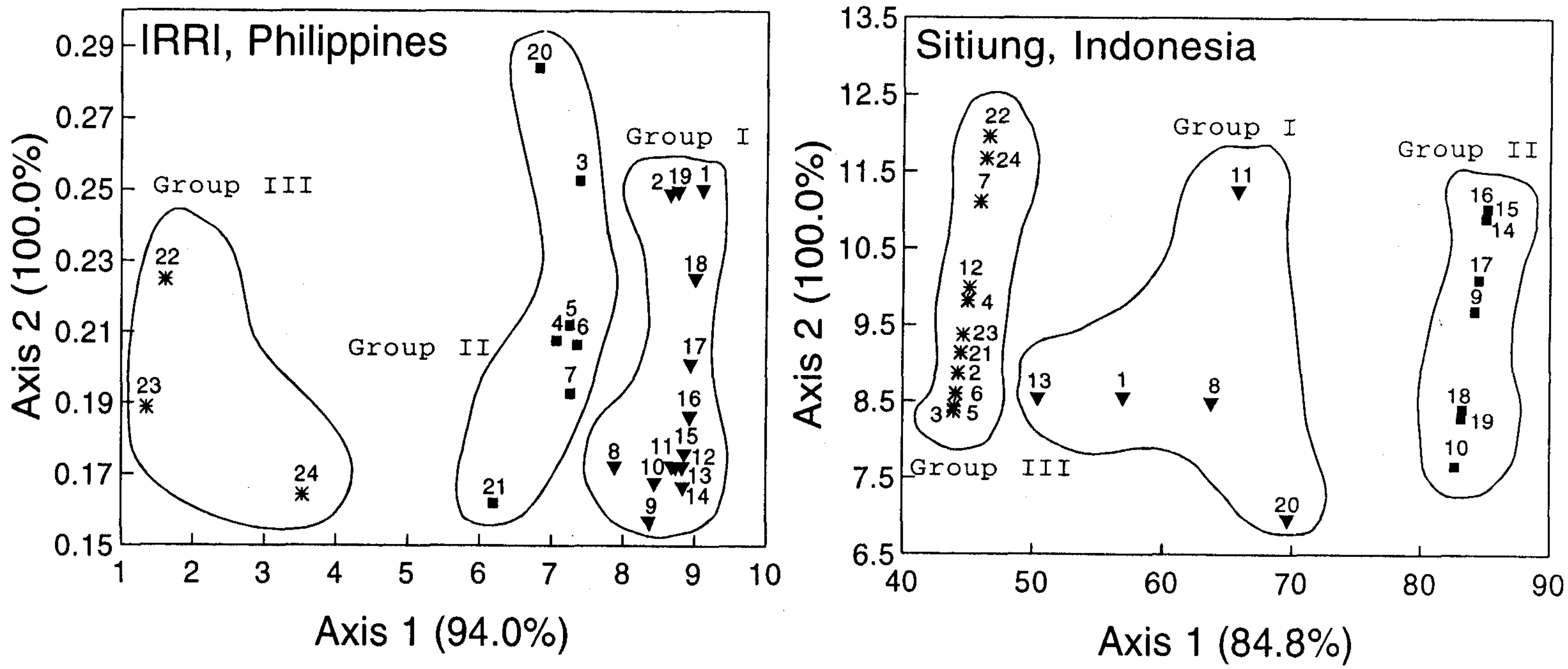


Fig. IV.2b. Ordination of 24 hypothetical sowing months at IRRI blast nursery, Philippines and Sitiung, Indonesia using blast parameters on IR50 amd C22 cultivars, respectively, as attributes for principal component analysis. Numbers in parentheses are the percent cumulative variances of principal component axes. Numbers beside the markers are the sowing dates, i.e. 1= January 1; 2= January 15; 3= February 1; and so on. Markers represent blast proneness groups identified by cluster analysis, i.e. Group I (▼); Group II (■); Group III (*).

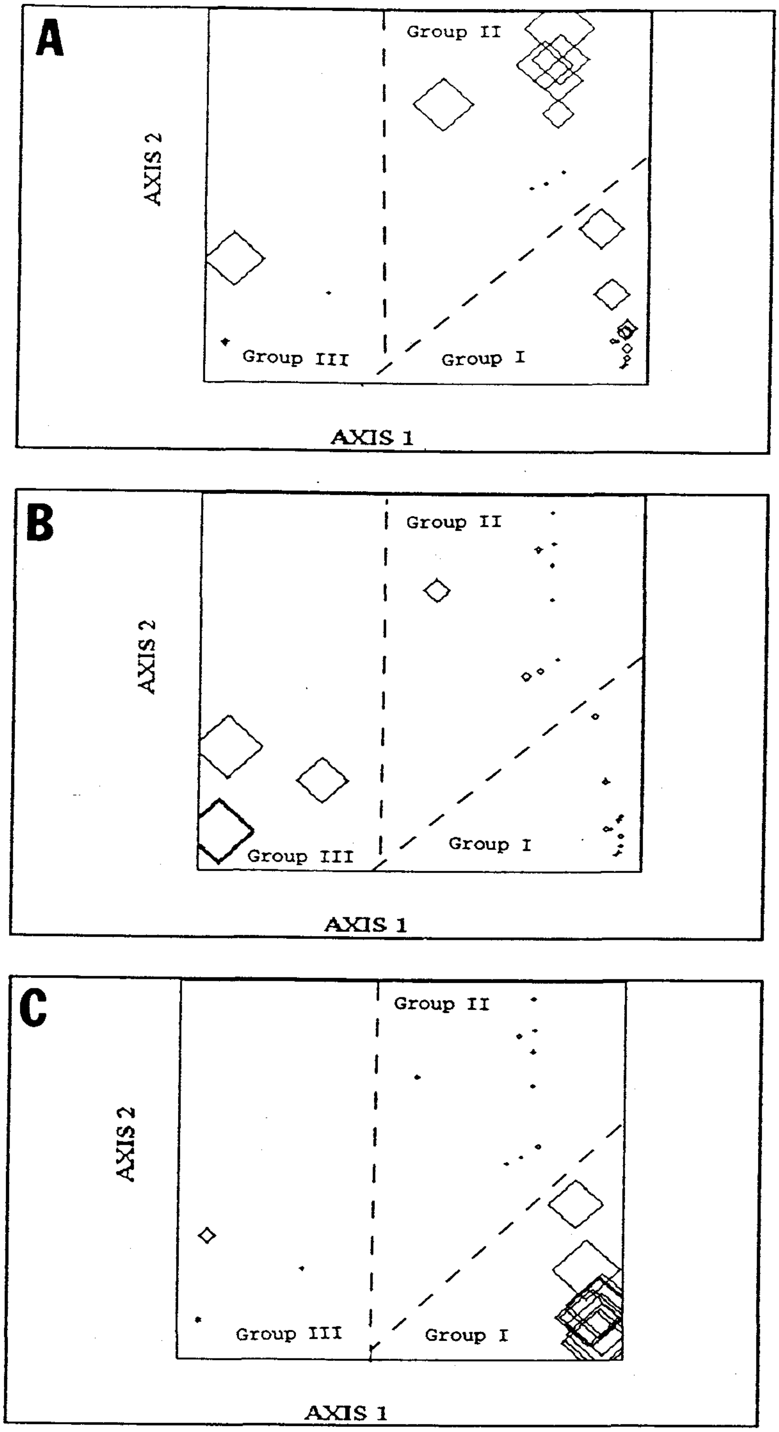


Fig. IV.3a. Ordination of 24 hypothetical sowing dates at Cavinti, Philippines when overlaid with **A**= maximum percent diseased leaf area; **B**= final percent diseased leaf area; and **C**= panicle blast severity (%) on C22 cultivar. Size of diamonds represents magnitude of blast proneness.

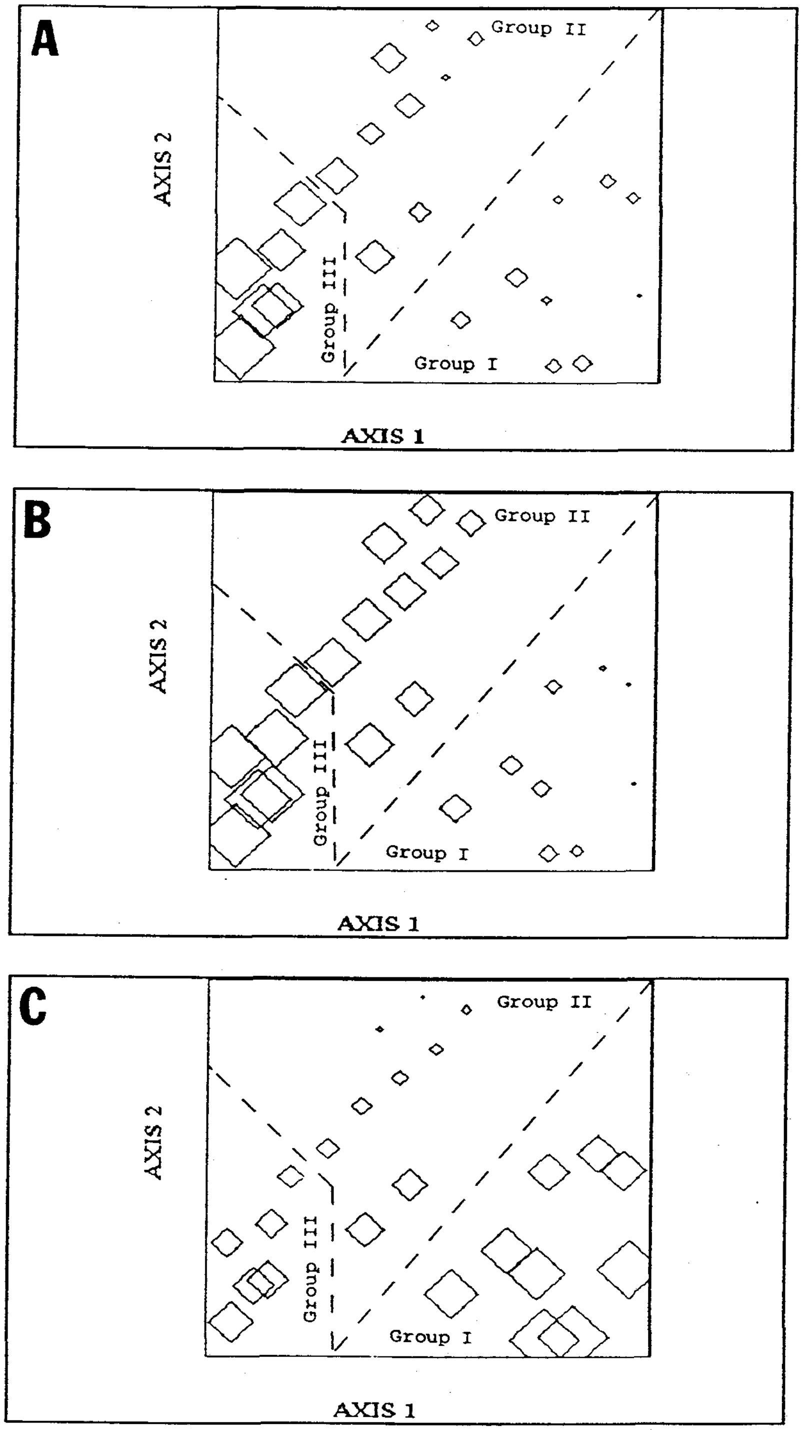
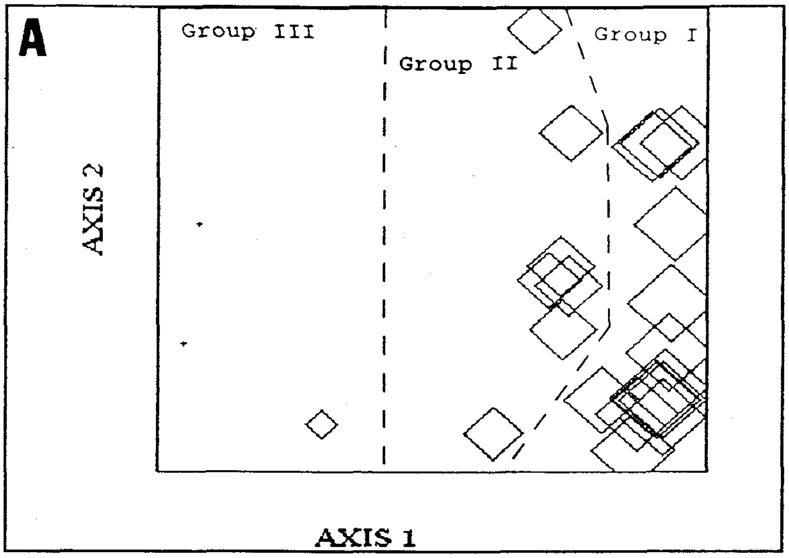


Fig. IV.3b. Ordination of 24 hypothetical sowing dates at Cavinti, Philippines when overlaid with **A**= maximum percent diseased leaf area; **B**= final percent diseased leaf area; and **C**= panicle blast severity (%) on IR50 cultivar. Size of diamonds represents magnitude of blast proneness.



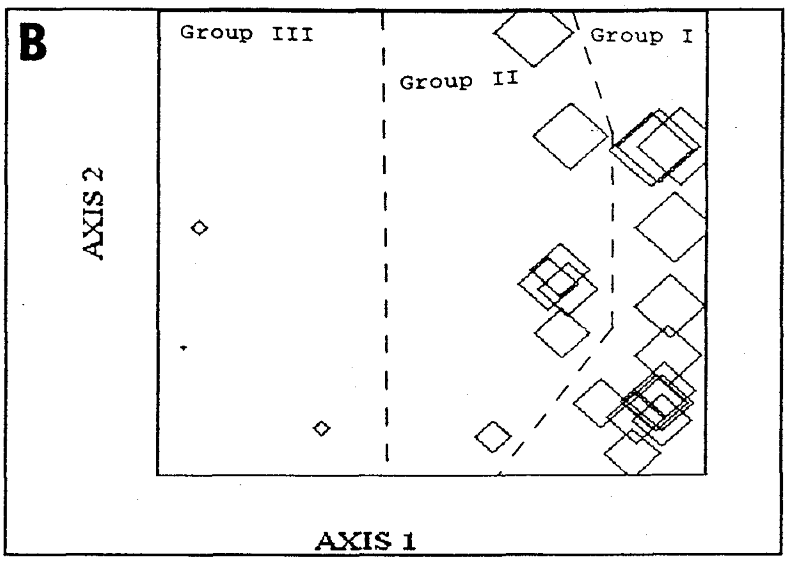


Fig. IV.3c. Ordination of 24 hypothetical sowing dates at the IRRI blast nursery, Philippines when overlaid with **A**= final disease leaf area and **B**= panicle blast severity (%) on IR50 cultivar. Size of diamonds represents magnitude of blast proneness.

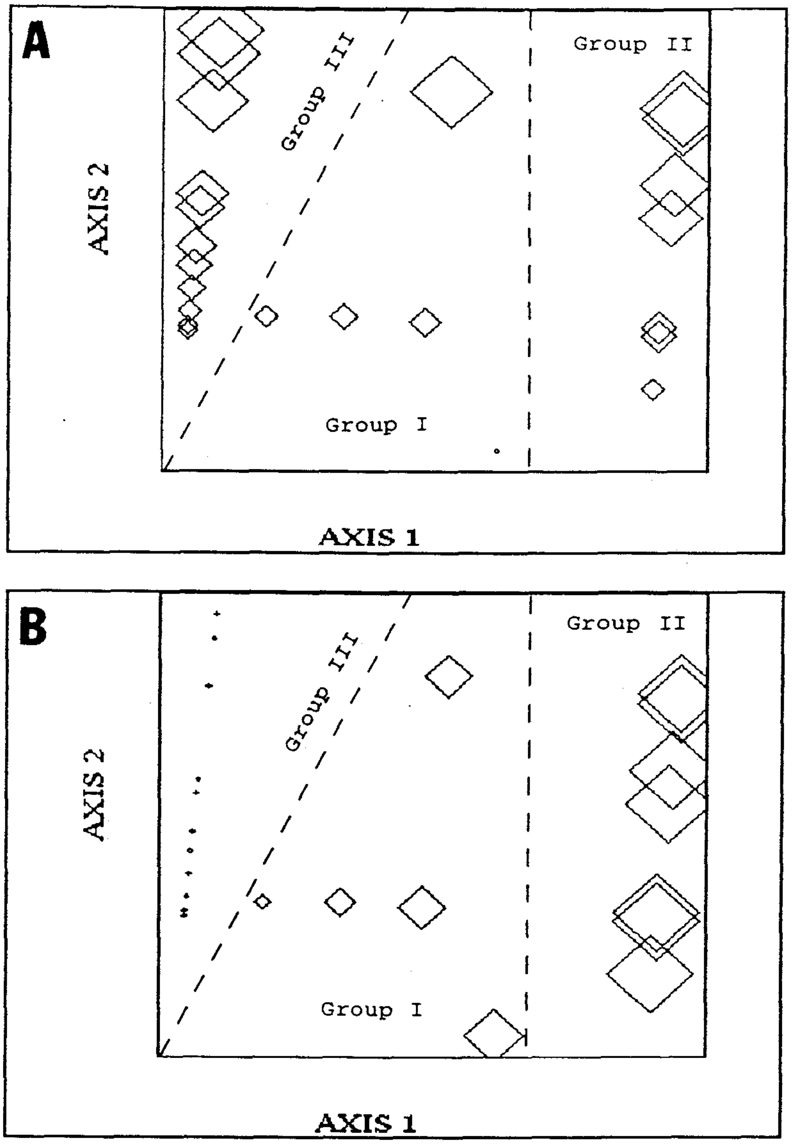


Fig. IV.3d. Ordination of 24 hypothetical sowing dates at Sitiung, West Sumatra, Indonesia when overlaid with **A**= final leaf blast index and **B**= panicle blast index on C22 cultivar. Size of diamonds represents magnitude of blast proneness.

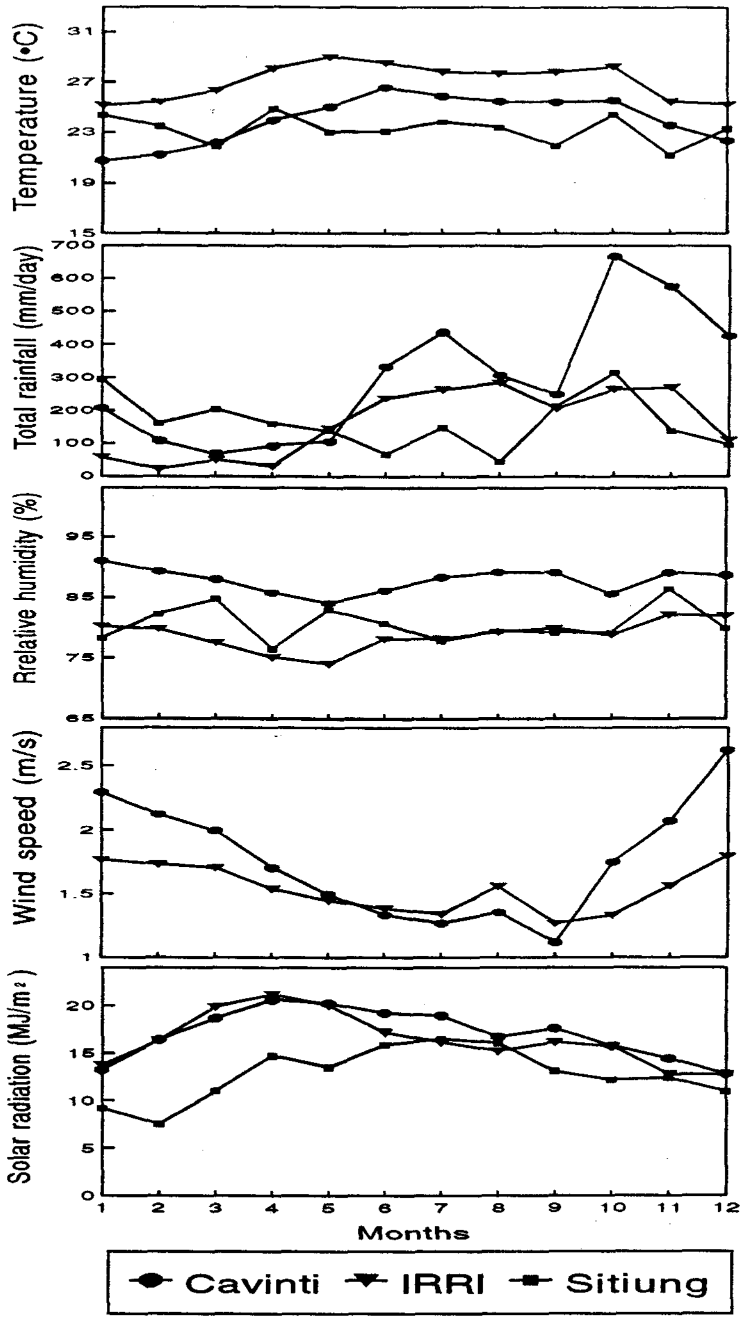


Fig. IV.4. Actual monthly mean values of weather variables at three Asian sites. There were two, seven, and eight years data at Sitiung, Cavinti, and IRRI, respectively. Sitiung had no wind speed data.

Table IV.1. Models used to predict blast parameters on susceptible cultivars that served as attributes in classification and ordination of 24 hypothetical sowing dates at Cavinti and the IRRI blast nursery in the Philippines and Sitiung, West Sumatra in Indonesia.[a]

Model $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n$	Statistics[b]				ACC[c]
	aR^2	PRESS	CV	P<W	(%)
Cavinti, Philippines - IR50					
MDLA[d]= (9.849 - 0.021*MMAX 10B16 - 0.459*DWS35 20B56$^{1/3}$ + 0.313 $N^{1/6}$)^2	0.61	0.95	2.19	0.14	94
FDLA= 35.113 - 8.804*DWS35 10B46 + 1.333*MRH 30A6 + 2.041*ln[e](N)	0.69	272.99	4.09	0.05	94
PBS= 2.486 - 0.0001*PFREQ 10A54^2 - 7.216x10^{-12}*N^4	0.72	0.02	1.67	0.23	80
Cavinti, Philippines - C22					
MDLA= (-8.478 + 3.467*ln(MMIN 10A5) - 0.017 PFREQ*30A3^4 + 3.606x10^{-9}*N^3)^5	0.96	0.30	7.17	0.62	87
FDLA= (-5.054 + 0.234*CDWP 20B37 + 0.0003*MSR 10A8^3 - 2.660x10^{-11}*N^4)^4	0.83	1.49	28.18	0.16	93
PBS= (1.819 + 0.010*$N^{1/2}$ - 2.485x10^{-10}*TPREC 50A24^4)^6	0.99	0.06	4.42	0.51	93
IRRI blast nursery, Philippines					
FDLA = -11210.000 + 5757.219*DG25C 20B57$^{1/6}$ - 0.049*CDWOP 10B35^2	0.52	14514.90	32.62	0.38	77
PBS = EXP[f](-95.177 + 50.783*DG25C 20B54$^{1/6}$ + 1.961x10-8*MRH 20B94^4)	0.29	2.04	5.77	0.23	62
Sitiung, Indonesia					
FLBIn = 8.502 - 0.268*TPREC 10A10$^{1/2}$	0.43	8.59	12.76	0.75	75
PBIn = 78.947 - 21.916*ln(DG25C 0B30)	0.72	0.02	1.67	0.23	80

Table IV.1. Footnotes

[a]Models were derived from regression analysis of rice blast parameters with meteorological factors as predictors. The convention used for predictor variables (X) indicates weather factors with beginning date after (A) or before (B) sowing and the time in days from the beginning date; e.g. DG25C $20B57^{1/6}$ indicates the number of days with maximum temperature greater than 25 C expressed in 6th root beginning 20 days before sowing with 57 days duration. MMAX= Average maximum temperature in C; DWS35= number of days with wind speed $\geq$ 3.5 m/s; N= nitrogen amount in kgN/ha; MRH= average relative humidity in percent; PFREQ= precipitation frequency in days; MMIN= average minimum temperature; CDWP= consecutive days with rainfall; MSR= average solar radiation in MJ/m^2; TPREC= total precipitation in mm/day; DG25C= Number of days with maximum temperature greater than 25 C; CDWOP= consecutive days without rainfall.
[b]aR^2= Adjusted coefficient of determination; PRESS= Allen's predicted residuals sum of squares; CV= coefficient of variation; Pr<W= Shapiro and Wilk's probability greater than W to test for normality among studentized residuals.
[c]Based on contingency quadrant where quadrants I, II, III, and IV suggest both actual and predicted disease parameter value to be moderate or light, actual value is severe but otherwise with predicted value, actual value is moderate or light but otherwise with predicted value, and both actual and predicted values are severe, respectively. In quadrants II and III, under and overprediction occur. Percentage accuracy (ACC) is calculated as $(a + b)/n$, where a and b are the number of observations falling in quadrants I and IV, respectively, and n is the total number of observations where predictions were made.
[d]MDLA= Percent maximum diseased leaf area; FDLA= percent final diseased leaf area; PBS= percent panicle blast severity; FLBIn= final leaf blast index; PBIn= panicle blast index.
[e]Natural logarithm function.
[f]Exponential function where e= 2.718.

Table IV.2. Group membership of 24 hypothetical sowing dates at Cavinti and the IRRI blast nursery, Philippines, and Sitiung, West Sumatra, Indonesia using rice blast parameters as attributes for classification by cluster analysis.[a]

		Cavinti		IRRI	Sitiung
Month	Day	C22[b]	IR50	IR50	C22
January	1	I	I	I	I
	15	I	I	I	III
February	1	I	I	II	III
	15	I	I	II	III
March	1	I	I	II	III
	15	I	I	II	III
April	1	I	I	II	III
	15	I	I	I	I
May	1	I	I	I	II
	15	II	I	I	II
June	1	II	II	I	I
	15	III	III	I	III
July	1	III	II	I	I
	15	III	II	I	II
August	1	III	II	I	II
	15	III	I	I	II
September	1	III	II	I	II
	15	II	II	I	II
October	1	II	II	I	II
	15	II	III	II	I
November	1	II	III	II	III
	15	II	II	III	III
December	1	II	II	III	III
	15	II	III	III	III

[a]I= Group 1; II= group 2; and III= group 3. Groupings were generated by slicing cluster dendrograms at specific distance measures.
[b]Cultivars used at the sites.

Table IV.3a. Pearson correlation coefficients of predicted rice blast disease parameter and meteorological factor variables with three ordination axes of 24 sowing dates for IR50 and C22 cultivars at Cavinti, Philippines.

Variable	IR50			C22		
	Axis			Axis		
	1	2	3	1	2	3
Disease parameter variables[a]						
MDLA	-0.89	-0.28	0.37	-0.08	0.75	0.66
FDLA	-0.99	-0.45	-0.01	-0.98	-0.20	0.08
PBS	0.43	-0.90	-0.01	0.61	-0.72	0.34
Meteorological factor variables[b]						
Rainfall						
$TPREC_o$	-0.44	0.70	-0.20	-0.68	0.44	-0.41
$PFREQ_o$	-0.11	0.78	0.12	-0.46	0.33	-0.47
$CDWP_o$	-0.10	0.83	0.08	-0.44	0.34	-0.47
$CDWOP_o$	0.13	-0.64	-0.18	0.44	-0.32	0.33
$DR84_o$	-0.25	0.53	-0.13	-0.57	0.16	-0.30
$TPREC_f$	-0.68	0.49	-0.21	-0.47	0.54	-0.20
$PFREQ_f$	-0.44	0.86	0.01	-0.58	0.40	-0.50
$CDWP_f$	-0.37	0.88	-0.04	-0.58	0.35	-0.54
$CDWOP_f$	0.53	-0.77	-0.08	0.54	-0.49	0.38
$DR84_f$	-0.62	0.41	0.01	-0.30	0.53	-0.22
Temperature						
$MMAX_o$	-0.76	-0.18	-0.15	-0.31	0.49	0.33
$DG25C_o$	-0.76	-0.07	-0.25	-0.29	0.53	0.19
$MMIN_o$	-0.73	-0.24	-0.25	-0.26	0.49	0.34
$MAVE_o$	-0.75	-0.20	-0.19	-0.29	0.49	0.34
$DOPT_o$	0.36	-0.21	-0.35	0.36	-0.21	-0.02
$CDOPT_o$	0.48	-0.12	-0.36	0.34	-0.30	-0.05
$MMAX_f$	-0.66	-0.58	-0.07	0.11	0.41	0.55
$DG25C_f$	-0.65	-0.57	-0.13	0.11	0.42	0.51
$MMIN_f$	-0.61	-0.62	-0.08	0.15	0.38	0.57
$MAVE_f$	-0.64	-0.59	-0.07	0.12	0.40	0.56
$DOPT_f$	0.55	-0.64	-0.03	0.58	-0.50	0.32
$CDOPT_f$	0.66	-0.47	-0.03	0.53	-0.57	0.15
Relative humidity						
MRH_o	0.34	0.11	0.15	0.18	-0.22	-0.34
$DRH80_o$	0.11	-0.13	0.02	0.25	-0.13	-0.27
$CDRH80_o$	0.11	-0.09	-0.05	0.14	-0.12	-0.24
MRH_f	0.55	0.27	-0.24	-0.01	-0.36	-0.09
$DRH80_f$	0.27	-0.36	-0.46	0.17	-0.20	0.44
$CDRH80_f$	0.29	-0.28	-0.53	0.16	-0.19	0.41

Table IV.3a. (continued)

Variable	IR50 Axis 1	IR50 Axis 2	IR50 Axis 3	C22 Axis 1	C22 Axis 2	C22 Axis 3
Meteorological factor variables						
Wind speed						
MWS_o	0.72	0.44	0.17	0.24	-0.36	-0.40
$DWS35_o$	0.85	0.12	0.06	0.39	-0.57	-0.14
MWS_f	0.55	0.67	0.14	-0.04	-0.26	-0.62
$DWS35_f$	0.81	0.32	0.13	0.23	-0.50	-0.39
Solar radiation						
MSR_o	-0.58	-0.35	-0.24	-0.24	0.30	0.53
MSR_f	-0.35	-0.76	-0.10	-0.31	0.16	0.64

[a]MDLA= Percent maximum diseased leaf area; FDLA= percent final diseased leaf area; PBS= percent panicle blast severity.
[b]Meteorological factors with subscripts "o" or "f" mean that these factors have duration from sowing to disease onset or sowing to flowering date, respectively. Disease onset for both cultivars was set at 24 days after sowing, whereas, for flowering date, IR50 has 80 days after sowing, while, C22 has 98 days after sowing. TPREC= Total precipitation in mm/day; PFREQ= precipitation frequency in days; CDWP= consecutive days with precipitation; CDWOP= consecutive days without precipitation; DR84= number of days with rainfall ≥ 84 mm/day; MMAX= average maximum temperature in C; DG25C= number of days with maximum temperature greater than 25 C; MMIN= average minimum temperature in C; MAVE= average mean temperature in C; DOPT= number of days with mena temperature range of 20-27 C; CDOPT= consecutive days with mean temperature range of 20-27 C; MRH= average relative humidity in percent; DRH80= number of days with relative humidity ≥ 80%; CDRH80= consecutive days with relative humidity ≥ 80%; MWS= average wind speed in m/s; DWS35= number of days with wind speed ≥ 3.5 m/s; MSR= average solar radiation in MJ/m^2.

Table IV.3b. Pearson correlation coefficients of predicted rice blast disease parameter and meteorological factor variables with two ordination axes of 24 sowing dates for IR50 cultivar at the IRRI blast nursery, Philippines.

Variable	Axes 1	Axes 2
Disease parameter variables[a]		
FDLA	0.99	-0.12
PBS	0.88	0.48
Meteorological factor variables[b]		
Rainfall		
$TPREC_o$	0.07	-0.28
$PFREQ_o$	0.08	-0.39
$CDWP_o$	0.14	-0.22
$CDWOP_o$	-0.01	0.42
$TPREC_f$	0.44	-0.49
$PFREQ_f$	0.32	-0.54
$CDWP_f$	0.42	-0.54
$CDWOP_f$	-0.20	0.53
Temperature		
$MMAX_o$	0.15	-0.21
$DG25C_o$	0.59	0.13
$MMIN_o$	0.67	-0.38
$DOPT_o$	-0.57	0.54
$CDOPT_o$	-0.58	0.55
$MAVE_o$	0.67	-0.37
$MMAX_f$	0.50	-0.60
$DG25C_f$	0.71	-0.21
$MMIN_f$	0.56	-0.57
$DOPT_f$	-0.46	0.66
$CDOPT_f$	-0.44	0.64
$MAVE_f$	0.53	-0.59
Relative humidity		
MRH_o	0.01	0.48
$DRH80_o$	-0.29	0.51
$CDRH80_o$	-0.25	0.44
MRH_f	0.71	0.55
$DRH80_f$	0.10	0.64
$CDRH80_f$	0.10	0.57

Table IV.3b. (continued)

Variable	Axes 1	Axes 2
Meteorological factor variables		
Wind speed		
MWS_o	-0.17	-0.41
$DWS35_o$	-0.26	-0.45
MWS_f	-0.14	-0.23
$DWS35_f$	-0.20	-0.15
Solar radiation		
MSR_o	0.47	-0.03
MSR_f	0.22	-0.04

[a]FDLA= Percent final diseased leaf area; PBS= percent panicle blast severity.
[b]Meteorological factors with subscripts "o" or "f" mean that these factors have duration from sowing to disease onset or sowing to flowering date, respectively. Disease onset for both cultivars was set at 24 days after sowing, whereas, for flowering date, IR50 has 80 days after sowing, while, C22 has 98 days after sowing. TPREC= Total precipitation in mm/day; PFREQ= precipitation frequency in days; CDWP= consecutive days with precipitation; CDWOP= consecutive days without precipitation; MMAX= average maximum temperature in C; DG25C= number of days with maximum temperature greater than 25 C; MMIN= average minimum temperature in C; MAVE= average mean temperature in C; DOPT= number of days with mena temperature range of 20-27 C; CDOPT= consecutive days with mean temperature range of 20-27 C; MRH= average relative humidity in percent; DRH80= number of days with relative humidity ≥ 80%; CDRH80= consecutive days with relative humidity ≥ 80%; MWS= average wind speed in m/s; DWS35= number of days with wind speed ≥ 3.5 m/s; MSR= average solar radiation in MJ/m².

Table IV.3c. Pearson correlation coefficients of predicted rice blast disease parameter and meteorological factor variables with two ordination axes of 24 sowing dates for C22 cultivar at Sitiung, West Sumatra, Indonesia.

Variable	Axes 1	Axes 2
Disease parameter variables[a]		
FLBIn	0.32	0.95
PBIn	0.99	-0.06
Meteorological factor variables[b]		
Rainfall		
$TPREC_o$	-0.54	-0.66
$PFREQ_o$	-0.51	-0.59
$CDWP_o$	-0.47	-0.53
$CDWOP_o$	0.53	0.60
$DR84_o$	-0.30	-0.22
$TPREC_f$	-0.55	-0.24
$PFREQ_f$	-0.45	-0.26
$CDWP_f$	-0.43	-0.25
$CDWOP_f$	0.44	0.26
$DR84_f$	-0.50	-0.26
Temperature		
$MMAX_o$	-0.79	-0.19
$DG25C_o$	-0.90	0.03
$MMIN_o$	-0.79	-0.24
$DOPT_o$	-0.57	0.15
$CDOPT_o$	-0.62	0.13
$MAVE_o$	-0.81	-0.21
$MMAX_f$	-0.68	-0.37
$DG25C_f$	-0.75	-0.21
$MMIN_f$	-0.64	-0.33
$DOPT_f$	-0.60	-0.22
$CDOPT_f$	-0.60	-0.24
$MAVE_f$	-0.67	-0.36
Relative humidity		
MRH_o	0.60	0.02
$DRH80_o$	0.56	0.09
$CDRH80_o$	0.53	0.04
MRH_f	0.48	0.41
$DRH80_f$	0.35	0.44
$CDRH80_f$	0.36	0.39

Table IV.3c. (continued)

Variable	Axes 1	Axes 2
Meteorological factor variables		
Solar radiation		
MSR_o	0.43	0.48
MSR_f	0.43	0.20

[a]FLBIn= Final leaf blast index; PBIn= panicle blast index.
[b]Meteorological factors with subscripts "o" or "f" mean that these factors have duration from sowing to disease onset or sowing to flowering date, respectively. Disease onset was set at 24 days after sowing, whereas, for flowering date, 70 days after sowing was used. TPREC= Total precipitation in mm/day; PFREQ= precipitation frequency in days; CDWP= consecutive days with precipitation; CDWOP= consecutive days without precipitation; DR84= number of days with rainfall ≥ 84 mm/day; MMAX= average maximum temperature in C; DG25C= number of days with maximum temperature greater than 25 C; MMIN= average minimum temperature in C; MAVE= average mean temperature in C; DOPT= number of days with mena temperature range of 20-27 C; CDOPT= consecutive days with mean temperature range of 20-27 C; MRH= average relative humidity in percent; DRH80= number of days with relative humidity ≥ 80%; CDRH80= consecutive days with relative humidity ≥ 80%; MSR= average solar radiation in MJ/m^2.

Table IV.4. Discriminant functions generated for Cavinti and the IRRI blast nursery, Philippines, and Sitiung, West Sumatra, Indonesia that classify 24 hypothetical sowing dates into three groups characterized by their proneness to blast outbreak.[a]

	Discrimininant function	E(AER)[b] (%)
Cavinti, Philippines		
LB[c]:	D(Group 1)[d] = -30.550 + 5.172 $DWS35_o$[e] + 0.510 $CDWP_o$ + 1.380 $CDOPT_o$	11.10
	D(Group 2) = -23.899 + 1.978 $DWS35_o$ + 1.455 $CDWP_o$ + 1.128 $CDOPT_o$	22.20
	D(Group 3) = -8.955 + 0.468 $DWS35_o$ +01.018 $CDWP_o$ + 0.670 $CDOPT_o$	16.70
IR50-PB:	D(Group 1) = -324.182 - 0.077 $TPREC_f$ + 4.088 $CDOPT_f$ + 22.719 $DWS35_o$ + 11.413 $MMAX_o$	0.00
	D(Group 2) = -180.529 - 0.043 $TPREC_f$ + 2.666 $CDOPT_f$ + 16.334 $DWS35_o$ + 8.890 $MMAX_o$	22.20
	D(Group 3) = -186.327 - 0.051 $TPREC_f$ + 2.581 $CDOPT_f$ + 15.107 $DWS35_o$ + 9.643 $MMAX_o$	16.67
C22-PB:	D(Group 1) = -3.406 + 1.296×10^{-4} $TPREC_o$ + 1.336 $DWS35_o$	0.00
	D(Group 2) = -6.920 + 0.038 $TPREC_o$ + 8.116×10^{-4} $DWS35_o$	33.33
	D(Group 3) = -10.453 + 0.047 $TPREC_o$ - 0.106 $DWS35_o$	50.00
IRRI blast nursery, Philippines		
LB:	D(Group 1) = -1518.000 + 178.731 $DG25C_o$ - 0.463 $CDWOP_o$	21.40
	D(Group 2) = -1517.000 + 178.440 $DG25C_o$ + 0.119 $CDWOP_o$	14.30
	D(Group 3) = -1345.000 + 168.229 $DG25C_o$ - 0.458 $CDWOP_o$	33.30
PB:	D(Group 1) = -29531.000 - 5.176 $DG25C_o$ + 835.639 $DG25C_f$ - 223.995 $PFREQ_f$	0.00
	D(Group 2) = -28454.000 - 1.319 $DG25C_o$ + 819.276 $DG25C_f$ - 219.292 $PFREQ_f$	29.00
	D(Group 3) = -28167.000 - 11.958 $DG25C_o$ + 817.796 $DG25C_f$ - 219.461 $PFREQ_f$	33.00
Sitiung, West Sumatra, Indonesia		
LB:	D(Group 1) = -98.849 + 9.090 $DG25C_o$	25.00
	D(Group 2) = -58.625 + 7.000 $DG25C_o$	12.50
	D(Group 3) = -120.358 + 10.030 $DG25C_o$	0.00
PB:	D(Group 1) = -521.579 + 13.912 $DG25C_o$ + 10.891 $DOPT_f$	25.00
	D(Group 2) = -405.206 + 11.366 $DG25C_o$ + 9.861 $DOPT_f$	12.50
	D(Group 3) = -546.686 + 14.873 $DG25C_o$ + 10.937 $DOPT_f$	0.00

Table IV.4. Footnotes

[a]Leaf and panicle blasts were recorded on different cultivars for the three sites. Cavinti had C22 and IR50 cultivars, whereas, IRRI blast nursery and Sitiung had IR50 and C22, respectively.
[b]Cross-validation error rate of missclassification, or the unbiased estimate of the expected actual error rate using Lachenbruch's holdout method (Johnson and Wichern, 1992).
[c]LB= Leaf blast; PB= panicle blast. At Cavinti, IR50 and C22 cultivars shared the same functions for allocating months into three leaf blast proneness groups.
[d]Discriminant function estimating classification of an observation to a particular group.
[e]Meteorological factors were generated via WINDOW PANE program using simulated daily weather data for each site. Factors with subscripts "o" and "f" mean that these have duration from sowing to disease onset and sowing to estimated flowering date, respectively. Disease onset was set to 24 days after sowing for all cultivars used at Cavinti and Sitiung, whereas, 17 days after sowing was used for IR50 at the IRRI blast nursery. Flowering date for IR50 was set to 75 and 80 days after sowing at the IRRI blast nursery and Cavinti, respectively, whereas, 70 and 98 days after sowing were used for C22 at Sitiung and Cavinti, respectively. DWS35= Number of days with wind speed ≥ 3.5 m/s; CDWP= consecutive days with precipitation; CDOPT= consecutive days with mean temperature range of 20-27 C; TPREC= total precipitation in mm/day; MMAX= average maximum temperature in C; CDWOP= consecutive days without precipitation; PFREQ= precipitation frequency in days; DOPT= number of days with mean temperature range of 20-27 C.

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CHAPTER V
SUMMARY AND CONCLUSIONS

The goals of this thesis were to develop empirical models that will predict rice blast and to identify innovative statistical approaches that can be used for developing a forecasting system for this disease. The research concern was directed at blast hot-spot areas. Statistical tools were used in three studies to quantify the influence of weather on blast so that disease prediction could be made. In Chapter II, the WINDOW PANE program was used to identify several weather factors as important predictors of blast. At Icheon in South Korea, the regression models selected to predict maximum leaf blast lesion number (ML) measured at 49 days after transplanting (DAT) on cultivar Jin heung are

$$ML1 = (0.01TPREC\ 7A19+2.09DRH80\ 5B34^{1/6})^{3}$$

$$ML2 = (6.48+0.12\log_e(CDRH80\ 3A2+1E\text{-}5)-0.51DOPT\ 13B10^{1/2}+0.63DRH80\ 3A2)^{3}$$

$$ML = (-7.06+5.47DRH80\ 1B30^{3}+27.09N)^{2}$$

where ML1 and ML2, respectively, are maximum lesion numbers under 110 kgN/ha and 220 kgN/ha; ML is maximum lesion number under combined nitrogen datasets; TPREC 7A19 is total precipitation (mm) during 7 DAT-26 DAT; DRH80 5B34, DRH80 3A2, and DRH80 1B30, respectively, are number of days with RH $\geq$ 80% with durations at five days before transplanting (DBT) to 29 DAT, 3 DAT-5 DAT, and 1 DBT-29 DAT; CDRH80 3A2 is consecutive days with RH $\geq$ 80% during 3 DAT-5 DAT; DOPT

13B10 is number of days with mean temperature range (C) with duration at 13 DBT-3 DBT; and N is nitrogen level at kgN/ha. The models selected to predict final leaf blast lesion number (FL) assessed at 68 DAT at Icheon are

$$FL1 = (0.94DRH80\ 5B40^{1/6}+8.71E\text{-}9TPREC\ 1B41^{3})^{6}$$

$$FL2 = (8.0+0.7CDRH80\ 3A20^{1/2}-6.17E\text{-}7DG25C\ 17B48^{4}-5.4E\text{-}4CDWOP\ 7A23^{3})^{2}$$

$$FL = (-1.37+1.01DRH80\ 5B34^{1/3}+0.07\ CDWP\ 7A24+0.01N)^{3}$$

where FL1 and FL2, respectively, are final lesion numbers under 110 kgN/ha and 220 kgN/ha; FL is final lesion number under combined datasets; DRH80 5B30 and DRH80 5B34, respectively, are number of days with RH ≥ 80% during 5 DBT-25 DAT and 5 DBT-29 DAT; TPREC 1B41 is total precipitation during 1 DBT-40 DAT; CDRH80 3A20 is consecutive days with RH ≥ 80% with duration at 3 DAT-23 DAT; DG25C 17B48 was number of days with maximum temperature (C) during 17 DBT-31 DAT; CDWOP 7A23 is consecutive days without precipitation during 7 DAT-30 DAT; CDWP is consecutive days with precipitation during 7 DAT-31 DAT; and N is nitrogen level. Lastly, the models selected to predict percent panicle blast incidence (PBI) measured at 84 DAT at Icheon are

$$PBI1 = 0.36TPREC\ 3A20$$

$$PBI2 = \exp(4.51-2.22E\text{-}5DRH80\ 25B70^{3})$$

$$PBI = (1.48-0.26DR84\ 25B63-3.71E\text{-}7CDRH80\ 9B51^{4}+0.003N)^{6}$$

where PBI1 and PBI2, respectively, are panicle blast incidence under 110 kgN/ha and 220 kgN/ha; PBI is panicle blast incidence under combined nitrogen datasets; TPREC 3A20 is total precipitation during 3 DAT-23 DAT; DRH80 25B70 is number of days with RH ≥ 80% during 25 DBT-45 DAT; DR84 25B63 is number of days with rainfall above 83 mm/day during 25 DBT-38 DAT; CDRH80 9B51 is consecutive days with RH ≥ 80% during 9 DBT-42 DAT; and N is nitrogen level.

At Cavinti in the Philippines, the regression models selected to predict percent maximum (MDLA) and final diseased leaf area (FDLA), and percent panicle blast severity (PBS) on cultivar IR50 are

$$MDLA = (9.85-0.02MMAX\ 10B16-0.46DWS35\ 20B56^{1/3}+0.31N^{1/6})^{2}$$

$$FDLA = -35.11-8.80DWS35\ 10B46+1.33MRH\ 30A6+2.041\log_e(N)$$

$$PBS = (2.41+0.015CDWP\ 40A39-3.0E\text{-}4PFREQ\ 10A54^{2})^{5}$$

where MDLA, FDLA, and PBS measured at 91 days after sowing (DAS), 124 DAS, and 124 DAS, respectively; MMAX 10B16 is average maximum temperature (C) during 10 DBT-6 DAT; DWS35 20B56 and DWS35 10B46, respectively, are number of days with wind speed above 3.4 m/s during 20 DBT-36 DAT and 10 DBT-36 DAT; MRH 30A6 is average RH during 30 DAT-36 DAT; CDWP 40A39 is consecutive days with precipitation during 40 DAT-79 DAT; PFREQ 10A54 is the number of wet day periods during 10 DAT-64 DAT; and N is nitrogen level. The regression models for blast on cultivar C22 at Cavinti are

$$MDLA = (-8.48+3.47\log_e(MMIN\ 10A5)-0.02PFREQ\ 30A3^{4}+3.61E\text{-}9N^{3})^{5}$$

$$FDLA = (-5.05+0.23CDWP\ 20B37+2.86E\text{-}4MSR\ 10A8^{3}-2.66E\text{-}11N^{4})^{4}$$

$$PBS = (1.82-2.49E\text{-}10TPREC\ 50A24^{4}+0.01N^{1/2})^{6}$$

where MDLA, FDLA, and PBS assessed at 83 DAS, 132 DAS, and 132 DAS, respectively; MMIN 10A5 is average minimum temperature (C) during 10 DAT-15 DAT; PFREQ 30A3 is the number of wet day periods during 30 DAT-33 DAT; CDWP 20B37 is consecutive days with precipitation during 20 DBT-17 DAT; MSR 10A8 is average solar radiation (mJ/m^2) during 10 DAT-18 DAT; TPREC 50A24 is total precipitation during 50 DAT-74 DAT; and N is nitrogen level.

At the IRRI blast nursery, Philippines, the models predicting final DLA (FDLA) and panicle blast severity (PBS) both occurring at 105 DAS are

$$FDLA = -11210+5757.22DG25C\ 20B57^{1/6}-0.05CDWOP\ 10B35^{2}$$

$$PBS = \exp(95.18+50.78DG25C\ 20B54^{1/6}+1.9E\text{-}8MRH\ 20B94^{4})$$

where DG25C 20B57 and DG25C 20B54, respectively, are the number of days with maximum temperature above 25 C during 20 DBT-37 DAT and 20 DBT-34 DAT; CDWOP 10B35 is consecutive days without precipitation during 10 DBT-25 DAT; and MRH 20B94 is average relative humidity during 20 DBT-79 DAT.

At Gunung Medan in Indonesia, only the panicle blast model was generated at this site which is

$$PBIn = 2.45+2.0E\text{-}4CDWP\ 1A62^{3}$$

where PBIn is panicle blast index on C22 measured at 100 DAS; and CDWP 1A62 is consecutive days with precipitation during 1 DAT-63 DAT. The weather factors correlated with leaf blast at Gunung Medan had no predictive characteristics and were not pursued for developing leaf blast models.

At Sitiung in Indonesia, leaf (LBIn) and panicle blast indices (PBIn) models are

$$LBIn = 8.50-0.27TPREC\ 10A10^{1/2}$$

$$PBIn = 78.95-21.92\log_e(DG25C\ 0B30)$$

where LBIn and PBIn measured at 68 DAS and 100 DAS, respectively; TPREC 10A10 is total precipitation during 10 DAT-20 DAT; and DG25C 0B30 is the number of days with maximum temperature above 25 C from sowing to 30 DAT.

The regression models above demonstrated that differences in weather requirements of blast occurred at different locations and in different cultivars at the same location. At Icheon, RH is important to blast. However, blast at the Philippines and Indonesian sites was influenced by four weather variables: rainfall, temperature, RH, and wind speed. Although these models were selected based on their level of precision (i.e. adjusted-R^2, PRESS, CV, VIF values) and accuracy in prediction (i.e. ACC), there are immediate problems in using these equations. First, the few disease observations available at the sites may restrict the models from representing the real disease trends as influenced by weather changes. Models may not predict disease accurately if the values of weather factors are outside the range of those used in generating the regression models. Second, the implicit assumption that a pathosystem consists of interacting components from the environment is refuted by models with only one predictor. This may be the case with the Indonesian models. Third, models developed for highly susceptible cultivars would have low values in statistical tests for significance. There are two causes of this: the less variation in severity values (as at Cavinti with IR50) and blast occurring at non-optimum conditions for disease development due to artificial inoculum that gave no clear linear relationship between weather and disease (as at the IRRI blast nursery). Lastly, there is always an existing gap between a biologically meaningful model and statistically significant model. Some models included a few predictor variables that were highly correlated with each other (multicollinear) or had statistically insignificant regression coefficients (β_n). These models, in a statistical sense, do not have good predictive abilities because of multicollinearity or insignificant β_n terms. In a biological sense, however, incorporating statistically insignificant explanatory variables may be feasible as long as these variables are biologically meaningful.

The path coefficient analysis in Chapter III showed that among the RH factors, the consecutive days with RH $\geq$ 80% (CDRH80) had a highest positive direct effect on leaf blast but a negative effect on panicle blast at Icheon. At Cavinti, blast on IR50 and C22 was directly influenced by different weather factors. Minimum temperature and consecutive days without rain had the largest direct positive effects on blast (leaf and panicle) on IR50. Total precipitation and increasing days of wind speed above 3.4 m/s had the largest positive effects on leaf blast on C22. Maximum temperature showed the largest negative effect on panicle blast on C22. The differences in factors affecting blast on the two cultivars were attributed to host predisposition and differences in *P. grisea* lineages infecting the cultivars. IR50 was more predisposed to infection than C22 at Cavinti. Since the experiment was conducted under upland conditions, the former, being a lowland cultivar, was not adapted to the growing conditions. For differences in pathogen lineages, it was found that IR50 is infected by lineage 7 of *P. grisea* at Cavinti, while C22 is infected by lineages 1, 4, and 17 at the same site (Dahu, 1993). Leaf and panicle blast on IR50 at the IRRI blast nursery were positively influenced by increasing days with maximum temperature above 25C and CDRH80, respectively. Although statistically valid, results of path analysis at the nursery can be misleading. The reason for this is that the nature of blast epidemic that developed at the nursery was regarded as artificial rather than natural. This was caused by the continued presence of inoculum sources at this site. Therefore, regardless of whether the weather conditions are favorable to blast or not, blast occurred continuously at the nursery. At the two Indonesian sites, differences in weather factors affecting panicle blast were also observed. At Gunung Medan, precipitation frequency had a direct positive effect on this disease parameter. At Sitiung, increasing days with mean temperature range of 20-27 C had the largest direct negative effect on panicle blast. Elevation could be an important factor why different weather factors affected blast at these sites. Sitiung is at a higher elevation than Gunung Medan. We postulated that races of *P. grisea* had developed adaptations to the conditions occurring specifically at the two sites. These made the pathogen respond differently at different sites.

Predicting proneness to blast of rice cultivars sown at different times of the year (Chapter IV) would be of value in blast management. Multivariate statistical procedures were employed to develop this approach in three tropical sites. In general, cultivar IR50 would be prone to leaf and panicle blast when planted at any time of the year at Cavinti. If planted at the blast nursery, this cultivar may have less infection during late November to December. However, since blast inocula are always present at the nursery, these results may be inconclusive. Undoubtedly, the continued presence of inoculum at the nursery and IR50 being a highly susceptible cultivar render the plant to be easily infected by *P. grisea* at this site. These factors obviously suggest that IR50 may always have high blast severity at the nursery, which is just the opposite of what was discovered using the multivariate analysis. With C22 at Cavinti, sowing this cultivar on mid-September, mid-November, and early December gave low proneness to leaf and panicle blast. At

Sitiung, the July 1 sowing was the only date on which C22 had both low leaf and panicle diseases. Sowing C22 at other sowing times at Cavinti and Sitiung either produced low leaf blast but high panicle blast or vice-versa.

Results using the multivariate techniques were all hypothetical. It is possible that the results from such techniques could be uncertain, i.e. blast proneness is actually different from what is observed in real field situations. Or, the results could also be valid and may actually predict the trend of proneness of cultivars to blast. The question on the validity of the multivariate methods can be addressed by using new disease and weather datasets. Since discriminant functions were generated to predict proneness of rice to blast as affected by weather factors, these equations could then be applied to determine the closeness of predicted blast proneness with actual proneness. At least two years of continuous planting can be used to validate the usefulness of the discriminant functions for predictions. For each year, there would be three growing seasons from where disease progressions are assessed. At the same time, daily weather data should be recorded in each year of growing season including the years immediately preceding and following this time. The weather factors needed by the discriminant functions will then be extracted from these weather data. Because the functions predict the blast proneness group (BPG), the actual leaf and panicle blast severities (S) should be converted to some measurement of proneness. A simple way is to make a rough three-scale proneness measurement (PMS): very prone (100% ≥ S ≥ 50%), moderate (49% ≥ S ≥ 20%), and less prone (19% ≥ S ≥ 0%). The PMS obtained at a particular sowing time should then be compared to the proneness characteristics of predicted BPG.

Models that were found appropriate for predictions require validation using field data so that their applicability at the sites is ascertained. The Indonesia models are relatively inferior compared to the models at Icheon and Cavinti because they were generated from a few observations. Similarly, the weather factors used to generate these models were extracted from simulated weather databases. However, this does not mean that such models are useless. Instead, the challenge would come when model-generated disease values are tested with real data. At the Indonesian sites, it is feasible to validate the models using miniplot (a plot of about 4 m^2) blast experiments conducted three or five times a year for 5 years or more. For each sowing time, disease progression should be assessed. The IRRI Climate Unit has started compiling weather data at Sitiung and therefore, availability of weather data at this site in the future will not be a problem. However, accessibility to the weather data at Gunung Medan is still uncertain.

There is a concern about the simplicity of these models in predicting blast in such complex crop production systems.

Previously, the effect of nitrogen on blast has been incorporated in some simulation models but not in empirical forecasting models. We have addressed this issue in this thesis by using nitrogen terms as explanatory variables in the models at Cavinti and Icheon. Such an inclusion either made improvements in the model fit or not (due to insignificant nitrogen regression coefficient). Nonetheless, inclusion of a nitrogen term in a model should account for its effect on blast. The soil silica content, plant type architecture, and initial amount of blast inoculum are also potential explanatory variables in predictive regression models. Quantifying these factors, however, is challenging due to the limited data available of these factors. Inclusion of these variables to regression models would also require large sample sizes (cases) to satisfy the case-to-explanatory variable (EV) ratio. The rule of thumb is 5 to 10 cases for every EV (Neter et al., 1989; Tabachnick and Fidell, 1989).

The applicability of the models developed to other locations and cultivars not used in the thesis needs research. It is proposed that a generalization procedure can be done where blast hot-spot areas are grouped according to the similarity in their physical environments. Another approach is to use Geographic Information Systems (GIS). GIS is a tool that identifies areas where blast is a problem using physical (weather, soil), biological (cultivars sown, existing pest and diseases), and socio-economic (infrastructure, demography) characteristics of the locations. Because this approach considers several elements of the agroecosystem, it will be the most appealing tool in forecasting blast. Similarly, rice cultivars can be grouped according to the similarity in agronomic characters and reactions to blast. Once location and cultivar groups have been identified, blast proneness or possibility of an outbreak can be predicted at a site or on cultivar representative of each group. The predicted proneness or disease severity should then be used to make a generalization of proneness to blast at the other sites or on the other cultivars belonging to that group. Several other factors need to be considered in rice blast forecasting. The issue of inoculum source and the ever changing genetic structure of blast population at tropical sites are factors that need more attention. Likewise, the influence of other weather factors such as solar radiation, sunshine duration, and soil water potential to the blast pathosystem has not been fully quantified. These should then be the focus of future blast forecasting research.

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