REVIEW

Rice blast forecasting models and their practical value: a review

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Summary. Rice, after wheat, is the second largest cereal crop, and is the most consumed major staple food for more people than any other crop. Rice blast (caused by *Pyricularia oryzae,* teleomorph *Magnaporthe grisea*) is the most destructive of all rice diseases, causing multi-million dollar losses every year. Chemical control of this disease remains the most effective rice blast management method. Many attempts have been made to develop models to forecast rice blast. A review of literature of the rice blast forecasting models revealed that 52 studies have been published, with the majority capable of predicting only leaf blast. The most frequent input variable has been air temperature, followed by relative humidity and rainfall. Critical factors for the pathogenesis, such as leaf wetness, nitrogen fertilization and variety resistance have had limited integration in the development of these models. This review reveals low rates of model application due to inaccuracies and uncertainties in the predictions. Five models are part of current operational forecasting systems in Japan, Korea and India. Development of in-field rice-specific weather stations, along with integration of leaf wetness and end-user interactive inputs should be considered. This review will be useful for modelers, users and stakeholders, to assist model development and selection of the most suitable models for the effective rice blast forecasting.

Key words: leaf disease, neck disease, pathosystem, prediction, leaf wetness.

Introduction

Rice (*Oryza sativa* L.), is one of the main world staple food crops. Although it is predominant in Asia, this crop has also been cultivated in Europe since the 15th century, mainly in Mediterranean countries including Italy, Spain, Portugal, Greece, and France (FAO, 2016). Rice blast, caused by the fungus *Pyricularia oryzae* Cavara [synonym *P. grisea* Sacc, teleomorph *Magnaporthe grisea* (Hebert) Barr], has been identified as one of the major rice cultivation constraints worldwide (Wang *et al.*, 2015). The blast fungus is capable of infecting rice at any stage of the host life cycle. The disease appears early as white to grey / brown leaf spots or lesions, followed by nodal rot and as neck blast, which can cause necrosis and

frequently breakage of the host panicles (Katsantonis *et al.*, 2007). As rice production expanded through Asia, Latin America and Africa, the disease followed the expansion, and now occurs in more than 85 countries (Wang and Valent, 2009; Bregaglio *et. al.*, 2016). Under favourable conditions, rice blast can be the most important rice disease in China, Japan and the USA, causing severe damage to rice yields (Groth, 2006; Noguchi *et al.*, 2006; Zeng *et al.*, 2009). Severe blast has expanded due to use of susceptible cultivars, irrigation, large amounts of nitrogen fertilization, sandy light soils and rice fields surrounded by sheltering trees (Long *et al.*, 2000; Greer and Webster, 2001; Groth, 2006). Moderate field infections can cause approx. 50% grain yield reductions. It has been estimated that *P. oryzae* destroys rice grain each year that would feed 60 million people (Devi and Sharma, 2010). Based on scientific / economic importance, the pathogen was characterized in 2012 as the most destructive fungus in the world. This was based on

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the factors: the fungus affects rice crops supplying half of the world's population, and the devastating nature of the infections. Furthermore, the pathogen is scientifically important because it has been developed as a model system for the study of the plant-pathogen interactions (Dean *et al.*, 2012).

To initiate rice blast, the *P. oryzae* has evolved a unique mechanism for conidium attachment to rice leaf surfaces. The disease can be severe during periods of cool temperatures and high moisture, while conidia do not germinate under direct sunlight (Ou, 1985). Cloudy overcast weather and dew encourage blast spread. Conidia remain viable during winter even under snow. Infected host residue is the most important source of the primary inoculum causing epidemics initiation (Jeyanandarajah and Seveviratne, 1991). Harmon and Latin (2001) found that survival of the fungus was greatly reduced during winter, but during spring, sporulation of the fungus occurred on plant debris. Dissemination of the fungus also involves a wide range of alternative host plants (Valent and Chumley, 1991). In temperate regions, infested rice seed, straw, and residues have been implicated as the most important overwintering sources of primary inoculum, although their impacts on initial disease development and distribution is not fully understood (Lamey, 1970; Kingsolver *et al.*, 1984; Ou, 1985; Agarwal *et al.*, 1989; Cloud and Lee, 1993; Lee, 1994; Manandhar *et al.*, 1998).

The first rice blast forecasting model was developed 67 years ago. Because of the continuing importance of the disease, the aims of the present review are: 1) to examine all the published rice blast forecasting models; 2) to investigate the operation and usability of each model; 3) to analyze the variables used in each model, to prioritize the most common input complexes as the reportedly most favourable; and 4) to conclude model success from usability records.

The rice blast pathosystem

The rice blast pathosystem consists of two interrelated subsystems: the leaf blast pathosystem and the neck blast pathosystem (Teng *et al.*, 1991; Teng, 1994; Sirithunya *et al.*, 2002; Savary *et al.*, 2006). Within each subsystem, vertical and horizontal host resistance operates. Thus, alloinfection from non-rice hosts and rice hosts that initiate epidemics is important for rice blast forecasting and disease management. Many leaf blast and neck blast simulation models have been reported, although their validation in diverse environments is still not definitive. Many empirical damage functions for blast losses are known, but their validation and use in disease management requires further analyses.

While the leaf blast and neck blast have common features, they have usually been treated separately, because of time discontinuity and because their relationship is not clearly defined. Separate models and forecast systems have therefore been developed for each pathosystem, since leaf blast predictions do not always cover neck blast. Alloinfection in each subsystem is thought to occur with inoculum from rice plants in the immediate vicinity, which have been successfully infected, or from non-rice hosts of the pathogen. Once alloinfection has occurred with an initial amount of disease, then disease severity increases via autoinfection (Van der Plank, 1963).

Relationships between leaf and neck blast have been partially documented, while many questions still remain unanswered since conclusions are controversial (Ou, 1985; Hwang *et al.*, 1987; Bonman, 1992; Zhu *et al.* 2005; Puri *et al.*, 2009; Ghatak *et al.*, 2013). One reason for contradictions in the correlation between leaf and neck blast is that very severe leaf blast, which causes plant senescence and panicle death, reduces the chances of developing neck blast. Although quantitative resistance against leaf blast is positively correlated with quantitative resistance to neck blast, some cultivars may be resistant to the disease on leaves, and relatively susceptible on panicles. *Pyricularia oryzae* conidia depositing onto panicle spikelets are the blast epidemic event considered to be more stochastic, driven by chance, than deterministic (Ishiguro and Hashimoto, 1991; Koizumi and Kato, 1991). Ishiguro and Hashimoto (1988) reported that although large numbers of conidia are released from lesions on leaves, they may or may not produce panicle blast infections even under favourable environmental conditions.

Environmental conditions and meteorological variables

Rice blast, is favoured by particular air and soil temperatures, relative humidity (RH), hours of continuous leaf wetness (LW), degree of light intensity and duration and timing of dark periods, all of which have been considered as very important for disease development. Many studies have reported ranges

and optimum conditions for the development of the disease. An overview of these conditions outlined in different studies is presented in Table 1.

The life cycle of *P. oryzae* begins with the deposition of conidia on rice plants. The conidia become tightly attached to the hydrophobic rice leaf surfaces in LW conditions (El Refaei, 1977). Mature lesions can produce conidia when RH is greater than 89%. High sporulation potential is possible at 20°C (Kato *et al.*, 1970; Kato, 1974; Kato and Kozaka, 1974; El Refaei, 1977). Sporulation is also favoured by cultivation of rice in aerobic soils or wetlands by long duration of LW due to drizzle or dew disposition, by little or no wind at night and by night temperatures between 17 and 23°C (Webster and Gunnell, 1992). Suzuki (1969c) observed that water is necessary for conidium dis-

charge; the more water droplets retained on infected leaves, the more conidia are released. Manandhar *et al.* (1998) concluded that seedlings grown under low temperature conditions (15 to 20°C) did not develop blast lesions, but when the same plants were transferred into warmer temperatures (25 to 30°C), blast lesions were detected. Numbers of conidia produced varied from 80,000 per spikelet lesion to 280,000 per neck node lesion, and sporulation potential is also related to the level of partial resistance in the host (Yeh and Bonman, 1986; Castaño *et al.*, 1989). Released conidia float under the rice plant canopy and then escape into the air above the canopy. After successful host invasion, the fungus colonizes host tissue, and visible symptoms appear in 5 d under favourable conditions (Ou, 1985).

Table 1. Range and optimum environmental conditions which favour rice blast development, as reported in the literature.

Condition	Stage	Range	Optimum
Leaf wetness	All stages	Always required	
Air Temperature	Appressorium germination	10–33 °C	25–28 °C
	Appressorium formation	21–30 °C	28 °C
	Lesion formation (wet leaves)		4–5 d at 25–28 °C
	Mycelium growth	8–37 °C	28 °C
	Mycelium survival for 18 months	-20– -30 °C	-30 °C
	Sporulation	9–35 °C	25–28 °C
	Dispersal of conidia		20.5–21.8 °C
	All stages at night	17–22 °C	20 °C
	Host blast susceptibility	10–30 °C	25–28 °C
Soil temperatures	Rice seedlings	20–30 °C	
	Adult plants	18–24 °C	
RH (air)	Mycelium growth		93 %
	Conidium germination	89–96 %	93 %
	Dispersal of conidia		90 %
	Disease development		93-95 %
Rainfall	All stages (direct effect)	Unclear	Unclear
Sunlight	Lesion formation		Night hours
Near-UV light	Germtube length	366–340 nm	366 nm
Carbon dioxide		Ambient +200–300 µmol mol^{-1}	

Rice blast management

Modern rice cropping practices in Europe include application of highly active nitrogen (N) fertilizers, such as urea (46% N). However, in conventional rice cropping, such highly active fertilizers are not recommended due to their breakdown effects on field resistance to blast (Ou, 1985; Freitas *et al.*, 2010). Management of blast has been extensively investigated, where different disease management strategies have been examined. These include: applying antagonistic *Pseudomonas*, *Bacillus* and *Streptomyces* spp. for biological control, (Prabavathy *et al.*, 2006; Tendulkar *et al.*, 2007; Karthikeyan and Gnanamanickam, 2008; Goud and Muralikrishnan, 2009; Filippi, *et al.* 2011; Khalil *et al.*, 2014; Meng *et al.*, 2015); using disease-resistant cultivars (Tokunaga, 1965; Villareal *et al.*, 1981; Koizumi and Kato, 1987); reducing N fertilizers (Ou, 1985; Long *et al.*, 2000); treating seed grains with chemicals (Yokoyama, 1981; Teng, 1994); using organic manure (Obilo *et al.*, 2012); applying triterpenoid glycosides derived from alfalfa (Abbruscato *et al.*, 2014); using neem seed extracts (Sireesha and Venkateswarlu, 2013), and using essential oils or extracts with antifungal properties (Sun *et al.*, 2014). Furthermore, other disease management methods have been reported, even when some exceptional techniques were introduced. For example, fan-forced wind into rice crop canopies to favour leaf dryness (Taguchi *et al.*, 2014), and intercropping with wild species (Wang *et al.*, 2007) have been tested. However, rice blast has never been eliminated from a region where rice is grown. A single change in crop management or in the way host resistance genes are deployed can result in significant disease losses, even after many years of successful disease control (TeBeest *et al.*, 2007).

Fungicide applications remain the dominant practice for controlling rice blast, sometimes using environmentally harmful chemicals or inducing fungicide resistance among pathogen populations (Todorova and Kozhuharova, 2010). However, the number of the available fungicide active ingredients is limited (Prabhu *et al.*, 2003; Kunova *et al.*, 2014; Chen *et al.*, 2015), since rice blast control does not attract appropriate interest of agrochemical companies. In a study in India, ten common active ingredients were tested for efficacy against rice blast, including dithane, carbendazim, propiconazole, mancozeb, wettable sulphur, thiophanate methyl, benomyl, ediphenphos, kitazine and tricyclazole. Only ediphenphos, kitazine and tricyclazole were effective for rice blast control, and only tricyclazole increased crop yield (Ganesh *et al.*, 2012). This chemical is a melanin biosynthesis inhibitor (Chen *et al.*, 2015), and was released in 1975 by Eli Lily/Dow for rice blast control, although initially suspected to have limited success because fungicide resistance in *P. oryzae* had been observed in China and Italy (Zhang *et al.*, 2006; Titone *et al.*, 2015). Nevertheless, this chemical remains the most efficient and most widely used blasticide among European rice growers, although it had to be withdrawn from EU use in March 2009, with a grace period expiring in March 2010.

Several concerns and questions have been raised regarding the environmental and human health impacts of tricyclazole along with the existing EU MRL. The fungicide is toxic (oral acute LD_{50} in mice = 245 mg kg^{-1}), and it has a long label-recommended residual period (54 d before harvesting; Froyd *et al.*, 1976; Tokousbalides and Sisler, 1978; Morton and Staub, 2008; EFSA, 2013; Gosetti *et al.*, 2014; Arora *et al.*, 2014; Fattahi *et al.*, 2015). In the EU, tricyclazole is banned but remains in circulation through the issue of 120 d short registrations at national levels, after demonstration of the effectiveness presented in the Commission. Currently, tricyclazole is banned from use in European rice cultivation. The EU MRL is 1.0 mg kg^{-1}, while in USA tricyclazole is banned. However, the USA import tolerance for the chemical is 3.0 mg kg^{-1} (http://globalmlr.com, assessed in 2016). Nevertheless, systemic fungicides are widely used to protect rice against leaf and neck blast when applied at the correct stage, to give optimum control with reduced environmental impact. The pesticide rate, and time and method of application depends on the information derived from accurate and timely forecasting of environmental conditions that are favourable for rice blast development.

Rice blast forecasting models

Disease forecasting allows prediction of probable outbreaks or increases in disease intensity, allowing if, when, and where a particular disease management practice should be applied (Agrios, 2005). Disease forecasting systems are based on assumptions concerning the particular pathogen's interactions with the host and the environment, the "disease triangle" of "virulent pathogen", "susceptible host" and "favourable environmental conditions".

There is no comprehensive way to classify all the disease models and modelling approaches used in agriculture. Researchers have initially indicated that most epidemic models are either analytic or simulations (Teng, 1985; Berger, 1989). An analytic model is simple, often with one equation with few biological variables, which can frequently be mathematically solved. Simulation models usually each comprise a series of equations that describe the behaviour of subsystems, and explicitly account for the influence of the environment at the subsystem level. They cannot commonly be solved using analytical (mathematical) techniques and require numerical solution with computer algorithms. Berger (1989) observed that some researchers (e.g., Teng and Zadocks, 1980) blended these two approaches, starting with analytic models and gradually increasing the degree of realism and the representativeness of the real world until each model was no longer amenable to an analytical solution.

In rice blast forecasting, Japanese research primarily considered inoculum intensity as determined by spore traps and plant predisposition (Yamaguchi, 1970). Predisposition to infection related to biological and ecological characteristics of plants for disease progression and degree of occurrence. In Thailand, spore trapping was established in blast-prone sites using trap plants instead of spore samplers. Disease severity was assessed on susceptible cultivars used as trap plants and effects of environment on variations in severity were evaluated. However, in the Philippines Pinnschmidt *et al.*, (1993) reported variations in the conidium numbers trapped by trap plants, compared to electronic and conventional spore trapping devices, due to weather effects. Similarly, viability of *P. oryzae* conidia from a spore trap differed from plant exposure because of environmental variations where spores were exposed prior to sampling (Bonman *et al.*, 1987; Pinnschmidt *et al.*, 1993).

Another approach was used for forecasting rice blast in India. Researchers had used information derived from planting susceptible cultivars at different times for several years (Chaudhary and Vishwadhar, 1988; Padhi and Chakrabarti, 1981). Similarly, Manibhushanrao *et al.* (1989) further studied effects of continuous planting of susceptible cultivars and weather on population structure of *P. oryzae*, to improve existing forecasting methodologies in that country.

The relationships of weather to above-canopy conidium numbers and plant predisposition to infection has been explored with the aid of computer modeling. Several statistical techniques have been used to develop reliable predictions. Models developed in Japan (Chiba, 1988; Uehara *et al.*, 1988; Ishiguro and Hashimoto, 1988, 1989; Ishiguro, 1991) were considered as extensive rice blast forecasting packages. Deterministic mathematical functions that relate weather conditions to leaf blast development via regression analysis, and stochastic probability models for panicle blast, were used to improve understanding of pathosystem dynamics. Regression analysis provided an excellent way of characterizing the environment as a few meaningful factors (Campbell and Madden, 1990). In Korea, computerized blast forecasting systems had also been implemented based on the relationship between aerial numbers of conidia, leaf blast infection, and meteorological variables as revealed by regression analysis (Kim, 1987; Kim *et al.*, 1987; Kim *et al.*, 1988; Lee *et al.*, 1989; Kim and Kim, 1991). Regression analysis had 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).

Path coefficient analysis is a technique in multivariate regression technique that is potentially useful in choosing which weather variable is the best disease predictor. This approach could identify direct and indirect effects of factors on disease without the confounding influences caused by multicollinearity. The analysis had 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 enabled measurement of the direct and indirect influences of one variable upon another. Mohanty *et al.* (1983), using path-coefficient analysis, positively correlated leaf angle, leaf pubescence, epicuticular wax and quantity of deposition of conidia with disease incidence. Torres and Teng (1993), similarly using path analysis, positively correlated leaf and neck blast with plant height and percentage of unfilled grains, while a significant effect of both symptoms was reported on plant yield reduction. Furthermore, they concluded that under field conditions, yield losses to rice blast could be estimated with more than 70% confidence through knowledge of the disease leaf area at the end of tillering stage and neck blast at harvesting.

Most rice blast forecasting models related weather variables to the occurrence and the development of disease, using statistical procedures. The choice of weather variables was mainly influenced by epidemic development. This is essential for successful application of forecasting schemes to wide-scale production areas. Table 2 presents an overview of forecasting models, which are categorized by weather variable inputs and the prediction type outputs.

Brief descriptions of the published models are presented in the next three sections, which represent the three forecasting category types: leaf blast, leaf and neck blast, and neck blast. Each section indexes the models according to prediction type, in chronological order of publication.

Leaf blast forecasting models

Leaf blast is the first major symptom that occurs following *P. oryzae* invasion. Forecasting favourable conditions for leaf blast is critical for early control and management of the disease. Thus, most published models aim to forecast leaf blast.

Decade 1970

In the 1970s and 1980s in Japan, researchers taking advantage of developments in computer hardware and software programming reported the development of computer simulation models to forecast rice blast (Fukuoka Agricultural Experiment Station, 1975; Hashimoto *et al.*, 1982, 1984; Oota, 1982; Takai *et al.*, 1985; Ishiguro 1986). However, these models were insufficient for quantifying the dispersion and the deposition of *P. oryzae* conidia within rice canopies, which is an important stage for the disease development (Koizumi and Kato, 1991). Limited information could be retrieved from the literature, since these studies were published in Japanese and the original papers were difficult to locate.

El Refaei (1977), in the Philippines, used data from blast nursery trials to develop several linear regression equations. He separately related numbers of lesions per seedling to weather variables, such as dew period, mean day or night temperatures, mean day or night RHs, and rainfall, along with airborne inoculum density. When conidia were incubated in water, an increase in germination was observed at optimum temperatures between 20 and 25°C. The model could forecast leaf blast 5 d in advance. The

set of equations showed exponential relationships between the disease, dew duration in hours and aerial conidium concentrations. However, this work was limited to nursery experiments. Furthermore, negative coefficients in the equations could not be biologically interpreted, and plant growth and ontogenetic changes in susceptibility were neglected.

An approach was developed by Yoshino (1979) in Japan, that has continued to be used. This determined *P. oryzae* infection periods, evaluating weather conditions every hour, and produced hourly results that indicated if the conditions would result in successful infections. The model was in two parts. The first contained three favourable conditions for successful conidium penetration and therefore successful infections:

1) the moving average of air temperature during past 5 d is 20-25°C

2) the rainfall to be below 4 mm h^{-1}, and

3) the continuous wet period >4 h than the base wet hours, calculated by the equation below:

Base wet hours = $60.09 - 4.216 \times temp_{wet} + 0.08858 \times temp_{wet}^2$,

(where $temp_{wet}$ is the air temperature when the leaves are wet)

The second part estimated the number of "infection hours", the hours where the three conditions of the first part are true. The infection hours for each day determined by the model were accumulated for 1 d, in order to calculate the daily infection warning hours (DIWH). The DIWH was categorized into four risk levels: 1) Zero Risk, DIWH = 0 h; 2) Low Risk, 1 h ≤ DIWH < 3 h; 3) Intermediate Risk, 3 h ≤ DIWH < 6 h; and 4) High Risk, DIWH ≥ 6 h. The Yoshino model is still used as part of three forecasting systems: a commercial system developed in Austria (http://www.fieldclimate.com), and in the models published by Kang *et al.*, (2010) and Kim *et al.*, (2015). Yoshiro's approach has also been adopted in five other published models, including those of Koshimizu (1983; 1988) and Hayashi and Koshimizu (1988); Tastra *et al.* (1987); Kim *et al.* (1987; 1988); Lee *et al.* (1989); and Ishiguro and Hashimoto (1988; 1989; 1991) and Ishiguro (1991).

Decade 1980

Hashimoto *et al.* (1982; 1984) developed BLASTL, using published data in combination with their own,

Table 2. Characteristics of 52 reviewed rice blast forecasting models, including their input variables, outputs and current useage.

Model references (alphabetic order)	Spore release	Sporulation	Spore penetration	Spore dissemination	Spore deposition	Leaf wetness	Air temperature	Relative humidity	Dew point	Rainfall	Sunlight	Phenological stage	Wind speed	In-field weather data	Host varieties	Nitrogen fertilization	Leaf blast	Neck blast	Currently in use / Operational
	Inputs																Outputs		
Ashizawa *et al.*, 2001																	X		
Ashizawa *et al.*, 2005				X	X	X	X			X	X	X	X		X	X	X		
Billoni *et al.*, 2006				X		X	X	X		X			X				X	X	
Bregaglio *et al.*, 2016						X	X	X		X			X				X	X	
Calvero and Teng, 1991, 1992	X	X	X		X			X				X					X		
Calvero *et al.*, 1996a							X	X		X	X			X	X	X	X	X	
Calvero *et al.*, 1996b												X					X	X	
Chiba *et al.*, 1966							X			X		X		X			X	X	
Choi *et al.*, 1988		X	X	X	X	X	X	X		X			X		X		X		
CRRI, 2013				X			X	X	X								X		X
El Refaei, 1977	X	X					X	X	X							X	X		
Fukuoka Agr. Exper. Station, 1975				X													X		
Gunther, 1986	X	X	X	X	X					X		X					X		X
Hashimoto *et al.*, 1984		X		X	X	X	X			X	X	X	X		X	X	X		X
Holcombe *et al.*, 2003			X														X		
Ishiguro and Hashimoto, 1988, 1989, 1991		X	X	X	X	X	X	X		X	X	X			X	X	X	X	
Ishiguro, 1986				X													X		
Izadyar and Baradaran, 1990							X								X		X		
Kanda, 2012							X	X		X	X	X	X				X	X	X
Kang *et al.*, 2010					X	X	X			X							X		X
Kapoor *et al.*, 2004							X	X		X	X	X		X			X	X	
Kaundal *et al.*, 2006							X	X		X							X		X
Kim and Kim, 1993	X	X	X	X			X	X	X	X		X		X			X		
Kim *et al.*, 1987, 1988						X	X	X							X	X	X		
Kim *et al.*, 2015						X	X	X		X		X					X		X
Koizumi and Kato, 1991	X	X		X	X									X			X	X	
Koshimizu, 1983, 1988						X	X	X		X	X		X				X		

(Continued)

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Table 2. (Continued).

Model references (alphabetic order)	Inputs																Outputs		Currently in use / Operational
	Spore release	Sporulation	Spore penetration	Spore dissemination	Spore deposition	Leaf wetness	Air temperature	Relative humidity	Dew point	Rainfall	Sunlight	Phenological stage	Wind speed	In-field weather data	Host varieties	Nitrogen fertilization	Leaf blast	Neck blast	
Kuribayashi and Ichikawa 1952					X												X	X	
Lanoiselet *et al.*, 2002							X	X		X							X		
Lee *et al.*, 1989						X	X	X	X	X	X			X			X	X	
Liang *et al.*, 2013		X					X	X				X					X	X	
Luo *et al.*, 1997							X	X	X	X	X						X		
Manibhushanrao and Krishnan, 1991		X	X				X	X	X								X		
Mousanejad *et al.*, 2009			X			X	X	X	X	X	X		X			X	X	X	
Ohta *et al.*, 1982, 1987		X	X	X	X	X	X	X		X			X	X	X		X		
Ono, 1965		X	X				X			X	X					X	X	X	
Oota, 1982					X												X		
Padmanabhan, 1965							X	X				X		X			X	X	
Park *et al.*, 1998	X				X	X	X	X		X	X	X	X	X			X	X	
Rafoss *et al.*, 2013							X	X		X	X		X	X			X	X	
Sasaki and Kato, 1972							X			X	X			X	X			X	
Savary *et al.*, 2012						X	X	X		X	X	X	X				X		
Surin *et al.*, 1991			X				X	X		X							X		
Suzuki, 1969b, 1974		X	X	X	X								X				X	X	
Takai *et al.*, 1985			X														X		
Takasaki, 1982			X	X														X	
Tastra *et al.*, 1987															X	X	X		
Torres, 1986		X	X	X			X		X			X				X	X		
Tsai and Su, 1984 and Tsai, 1986							X		X								X		
Uehara, 1985							X			X	X		X				X	X	
Yoshino, 1979						X	X			X							X		X
Zhejiang Research Group, 1986							X	X		X	X	X	X	X	X				

conducted in simulation units. This was probably the first simulation leaf blast model developed. Life cycle stages of *P. oryzae*, sporulation, conidium discharge, dissemination and deposition, blast infection and lesion development were simulated in relation to weather conditions, plant growth, leaf position, and host susceptibility as affected by weather, fertilizer application, plant or leaf age and leaf position. The dynamics of leaf blast were calculated as temporal changes in the number of lesions. Air temperature, rainfall, wind, sunlight duration and wetness period were used to feed the model, and additionally meteorological data were collected from the Automated Meteorological Data Acquisition System (AMeDAS). Time was advanced every 3 h. Leaf blast infection was measured by the number of lesions, while leaf area was assessed in field surveys. The model also included other variables, such as susceptibility index of leaves and initial inoculum dynamics, which were determined by observing the disease epidemics. This model was developed to assist farmers in applying control measures, and the model could predict leaf blast outbreaks in 7 d short-term forecasts. The model was tested in prefectures of Japan for several years, and was useful and practical. Since it contained a fungicide sub-model, it was also a practical tool for determining the timing and the efficiency of fungicide applications (Takai *et al.*, 1985; Ishiguro *et al.*, 1988). However, lshiguro and Hashimoto (1990) concluded that BLASTL required further improvements, to estimate the parameters which were first determined by trial and error procedures. Furthermore, the model could be improved through integration of a module that included the initial prediction of leaf blast epidemics.

The rice blast simulation model BLASTCAST was developed by Ohta *et al.* (1982; 1987) in Japan, which was a plant disease simulator similar to that of Hashimoto *et al.* (1982; 1984). BLASTCAST involved variables such as conidium production, dissemination, attachment, penetration and blast severity. Additionally, it collected daily data on host variables, such as lesion formation, variability of resistance to leaf blast and lesion incubation period. Hourly recorded field meteorological data were also collected, including humidity, wind speed, precipitation and LW. The model gave satisfactory results in the years 1973-1976 and 1979-1981. The authors concluded that increasing the amount of input data and including rice varietal resistance

would improve the model, although these developments have not been reported.

Koshimizu (1983; 1988) and Hayashi and Koshimizu (1988) developed BLASTAM as a software tool to predict rice leaf blast epidemics in Japan. This relied on hourly weather data collected from 840 sites from throughout the country using AMeDAS. The meteorological variables used were: air temperature, precipitation, (> 1 mm h^{-1}), sunshine duration and wind force. The model also used variables of LW period, mean temperature during LW and mean temperature of the five preceding days, along with other secondary weather variables, which met certain model criteria. The model first estimated LW conditions using AMeDAS, and subsequently determined the infection potential through relationships between the estimated LW condition and the surface air temperature. When evaluating the effects of climate change on LW, BLASTAM encountered many of the aforementioned difficulties that are typical of empirical models. The model classified favourable to unfavourable weather for infection, 7 d after the onset of the conditions. The BLASTAM approach was similar to that of the Yoshino (1979) model. The model is currently reported by the http://www.rei-gai.affrc.go.jp as operational for leaf blast prediction, using data from AMeDaS.

A forecasting model was also developed in Taiwan by Tsai and Su (1984) and Tsai (1986). This used multiple regression equations to analyze relationships between meteorological variables and the percentage of leaf area infected by *P. oryzae*, developing an early disease warning system. The equations contained three to four meteorological variables, such as average RH hours when RH was over 90 %, rainfall and number of rainy days. Model operation required that average RH, hours of RH over 90% and rainfall were the most influential factors for predicting blast severity. However, the model's equations have not been further validated or used in rice fields.

The model PYRICULARIA described by Gunther (1986) was a systematic theoretical approach written in a Continuous System Modelling Program (1972). It was a polycyclic leaf blast simulation model developed using information available from the literature, and it derived structural data from experiments carried out in temperate ecosystems. The model simulated phases of the *P. oryzae* life cycle, including conidium formation, free and resident conidia, conidium deposition and germination, appressorium

in FORTRAN IV, and included six input subroutines. These were: 1) conidium germination, 2) infection, 3) latent period, 4) lesion expansion, 5) conidium production, 6) dissemination. Another four output subroutines were also used, including: 1) for initialization, 2) leaf area calculation, 3) numerical and 4) graphic outputs. The results were tested on two rice nursery plots. Leaf blast progress was computed in terms of lesion number and disease severity. The model was successfully validated on two rice nursery datasets and in crops for only one rice cultivar. Ontogenetic and environmentally-associated changes in host susceptibility were not considered. Choi *et al.* (1988) concluded that LEAFBLST should be modified to accommodate incoming inoculum dispersed from surrounding infected fields, and to include temporal changes in host plant susceptibility. However, no further development of this model has been reported.

Decade 1990

A dynamic simulation model was developed by Koizumi and Kato (1991) at the National Agriculture Research Center in Tsukuba, Japan. This quantified dispersal and deposition of conidia over rice canopies. Microclimates inside rice cropping systems were considered. The simulation was based on data derived from the distribution of conidia from leaf lesions through sporulation and release. Wind velocity and turbulent diffusion coefficients were estimated at the canopy level. Conidium deposition and washing off during rain for every hour from 13:00 to 12:00 the next day were included. The model consisted of six subroutines, written in Microsoft FORTRAN, including: 1) weather, 2) canopy structure, 3) wind velocity and turbulence, 4) conidiophores and conidium formation, 5) conidium discharge and 6) residual conidium concentration. Experimental data were integrated using equations derived by previous publications (Uchijima, 1962; Inoue, 1963; Horie, 1981). Dispersal and deposition of conidia within or above rice canopies were simulated by modifying a model developed for barley (Legg and Powell, 1979). Suzuki (1969a) studied the effects of windspeed on the liberation, dispersion, and deposition of *P. oryzae* conidia in a rice crop. Koizumi and Kato (1991) suggested that windspeed and leaf area indices could affect conidium production, and, consequently, conidium concentration in the air. These factors could

influence the number of conidia attached on the leaves of susceptible rice plants.

Izadyar and Baradaran (1990) studied rice blast on five local cultivars transplanted four times with 6–7 d intervals, for 6 years in Iran. At every sowing date, minimum temperature and the number of days after transplanting (NDAT) were recorded until the appearance of leaf blast lesions. Regression models were generated to establish relationships between NDAT and both maximum leaf blast severity and minimum temperature. Model predictions showed increases in leaf blast severity due to decreases in the NDAT and increases in minimum temperature. There was a negative correlation between days after transplanting to appearance of leaf blast symptoms in the field and the average of minimum temperature during the same period.

An empirical forecasting model was developed in Thailand by Surin *et al.* (1991). Microscope slides from spore traps placed 80 cm above ground in several fields, were used to collect *P. oryzae* conidia at each growth stage of the crops. The number of conidia was correlated with disease severity, in combination with the weather conditions. When conidia numbered more than five per slide, blast occurred in that field after a period ranging from 7 to 15 d. The model correlated rice varieties with climatic conditions, such as temperature, RH, rainfall, and the number of conidia and blast occurrence. Optimum conditions for rice blast development were considered to be RH of 90% or greater and temperature between 25 and 28°C. A method of estimating blast severity was developed by measuring blast on the top four plant leaves. The close relationship between severity on the 3rd leaf and the average severity on all leaves indicated that samples taken from the 3rd leaf could be used as the basis for fungicide application decisions, and for crop loss assessments. Direct guidelines were developed to assist the farmers to control the disease.

EPIBLA (EPIdemiology of BLAst) simulated incidence of blast in India, and made 7-d forecasts of disease progression in tropical rice cultivation areas of that country (Manibhushanrao and Krishnan, 1991). This model was developed using multiple regression equations. Daily values of maximum temperature and maximum RH were used as predictors of numbers of conidia in the air. The predicted conidium amounts, the minimum temperature and the amount of dew, summed and averaged over the 7-d period

preceding disease onset, were used to estimate disease incidence. Three equations were proposed: one for predicting the number of airborne spores, and the other two for predicting disease progress. It was confirmed that disease susceptibility was related to plant age. Positive correlation was found between the amount of dew and minimum temperature. However, the model was developed using only two rice varieties, IR50 and IR20. Improvement of the accuracy of prediction required further reformulation using feedback from at least two growing seasons combining data derived from the field and from growth chambers.

BLASTSIM.2 was developed in the Philippines by Calvero and Teng (1991; 1992). This simulated leaf blast monocycle epidemics based on crop growth and weather conditions in different tropical rice management systems. The model had two main components: the blast simulation, in which the state values were computed, and the dew period simulation component, which predicted dew periods and the amount per day using the program DEWFOR (Luo and Goudriaan, 1991). BLASTSIM.2 followed the leaf blast factors such as, conidium production, release, deposition, and latency, pathogen penetration and colonization, and lesion production and development. Other included data were derived from interactive climatic, edaphic and agronomic factors considered to affect rice blast. The model was successfully validated in 1989 to accurately simulate leaf blast progressions in nursery trials with high correlation co-efficients. One limitation was that the model did not include a crop growth subroutine. After the trials, the authors concluded that BLASTSIM.2 could mimic the rice leaf blast pathosystem. However, further validation was needed in various locations, because data collections were derived only from nursery trials. Consequently, Luo *et al.* (1993) carried out blast surveys to determine the intensity of disease at specific locations, and assess whether models accurately estimated the disease. They included BLASTSIM.2 in their surveys. Also, GIS was used to superimpose the effect of UV-B radiation on BLASTSIM.2-generated blast progressions, converted into area under disease progress curve units. The GIS-generated raster maps of several Asian countries revealed possible blast prone areas. Their results were compared with actual blast incidence at those sites. The results confirmed that BLASTSIM.2 correctly simulated the expected blast-prone locations in tropical and temperate Asian countries. However, there are no reports of further development or use of this model.

EPIBLAST was published by Kim and Kim (1993) in Korea. The model was developed by collecting field rice blast epidemiological and meteorological data. The model comprised three groups of input variables: 1) meteorological (temperature, RH, rainfall, dew period and wind velocity); 2) plant physiological state (healthy, diseased and dead leaf area); and 3) epidemiological processes (inoculum potential, sporulation, conidium release and dispersal, penetration and incubation period). Validation tests of EPIBLAST during the 1990 crop season indicated that the model needed corrections for sporulation potential under natural conditions, to improve predictions to better fit actual leaf blast outbreaks. The accuracy of EPIBLAST was validated during 1991, and the model predicted field leaf blast epidemics. However, some fluctuations were observed, particularly when weather was changing rapidly, and Kim and Kim (1993) stated that further revision of the model was required.

A combined model simulation that studied effects of leaf blast epidemics on yield loses was developed by Luo *et al.* (1997). Historical daily weather data were collected from 53 locations in Japan, Korea, China, Thailand and the Philippines. Two simulation models were used: CERES-Rice, a growth simulation model, and BLASTSIM (Calvero and Teng, 1992). These were combined by linking the effects of leaf blast on rice leaf photosynthesis and biomass production. BLASTSIM was modified by adding new subroutines or modifying the existing ones. Two weather generators, derived from the Decision Support System for Agro-technology Transfer, were utilized to produce estimated daily weather data to run in the combined model. The two weather generators and the estimation methods were applied to produce a complete set of estimated weather data required by the combined model, including temperature, solar radiation, humidity, windspeed, rainfall, dew period, cloudiness and soil temperature. The combined model also simulated daily incidence and severity of leaf blast and crop growth parameters such as root weight, green leaf area, dead leaf biomass and grain weight. Thirty years of historic daily weather data were used as inputs to simulate blast epidemics for each temperature change based on the Monte Carlo method, for each of the generators for

every location. The outputs included disease severity, the area under disease pressure and yield loss. Temperature was the most sensitive variable in the model, while precipitation was insensitive. However, the ability to simulate rainfall effects to estimate dew formation and rice blast epidemics was limited. Luo *et al.* (1997) concluded that elevated temperature increased maximum blast severity and epidemics in cool subtropical zones, but inhibited disease development in warm humid subtropics. GIS graphics showing scenarios of blast epidemics for each country were produced from the simulated information for several locations for each country, using spatial interpolated methods. The model could not produce accurate yield loss forecasts because it failed to predict collar and panicle blast. No further development of this model has been published.

Decade 2000

In 2001 a simulation model was developed for forecasting leaf blast epidemics in rice multi-lines by Ashizawa *et al.* (2001). Very little information on this model can be retrieved as it was published in Japanese and is not available from the Web.

Lanoiselet *et al.* (2002) developed a different model approach to evaluate the risks of rice blast in Australia. Two climate simulation software programs, DYMEX and CLIMEX, were used to investigate risk of potential infection and sporulation of the rice *P. oryzae*. An area with typical climate for Australian rice cultivation was chosen for comparison to other foreign locations where rice blast occurs. Comparisons were carried out using temperature, RH and rainfall data. Additionally, a rice blast model was developed using the software DYMEX to predict the behavior of the pathogen in the rice-growing area of the country. The model was operated for the period 1988 to 1999, using the meteorological data of four representative Australian rice-growing locations. CLIMEX results were confirmed as the most suitable, and these highlighted the hypothetical threat of rice blast in Australia. This approach theoretical, while some validations were achieved for simulated data with real rice blast records in certain areas. However, the model needed datasets from real canopy conditions to give improved disease predictions.

Holcombe *et al.* (2003) specified the individuality of the *P. oryzae* pathosystem, considering the way the fungus invades host plants and propagates. They developed a simple model by applying hybrid computational techniques, using computer simulation and automated analysis to understand the behaviour of this complex biological system. They concluded that a fundamental problem was the understanding of the complex interactions between the different subsystems. They have expressed doubts about capability of understanding and analyses of the model, even when it was correctly constructed. They also stated that long term research covering 5 to 10 years was required to build realistic models.

Ashizawa *et al.* (2005) developed BLASTMUL in Japan. This model modified BLASTL (Hashimoto *et al.*, 1984). The model mimicked leaf blast epidemics in "Sasanishiki" and "Koshihikari" rice multilines, giving a very specific orientation. BLASTL was considered reliable. They stated that rice blast resistance was low in Japan, and that chemical control was the major disease management practice in Japan. For this reason, mixtures of near-isogenic lines (NILs) with different complete resistance (multilines) had been released. For the modification, new variables such as conidium dispersion and deposition were added to the model developed by Ashizawa *et al.* (2001). The new model calculated the numbers of lesions per crop subunit, for mixtures of susceptible and resistant NILs in given proportions, under various weather conditions. BLASTMUL was appropriate for evaluating rice mixtures for blast control in different locations and cultivars. The model could contribute to clarifying the stable use of blast resistance. However, the accumulated epidemiological data revealed the need to integrate more reliable variables in the model.

Kaundal *et al.* (2006) developed a model based on machine learning techniques for rice blast forecasting in India. They selected six significant weather variables, temperature (minimum and maximum), RH (minimum and maximum), rainfall and rainy days per week. They introduced a new forecasting method based on the powerful machine learning technique Support Vector Machines (SVM). This had been developed by Vapnik and coworkers, and was considered effective for general purpose supervised predictions (Cortes and Vapnik, 1995). Among the weather variables, rainfall was shown to be the best predictor, followed by relative humidity and rainy days per week. Temperature was found to have the least effect on disease development. This disagreed with most published models, where tem-

perature, especially low temperature, was indicated as one of the most critical variables for the disease development. Kaundal *et al.* (2006) concluded that the developed SVM was better for forecasting plant diseases than other existing machine learning techniques and conventional REG approaches. They have also developed an SVM-based web server for rice blast forecasting, the first of its kind, which can assist decision making. The server is available online at http://www.imtech.res.in/raghava/rb-pred/submit.html. The web-based model can predict leaf blast severity as percentage. Users input temperature, RH (minimum and maximum), rainfall and number of rainy days per week. However, percentage leaf blast severity output can be difficult to interpret where no limits and threshold information are provided.

Decade 2010

A forecasting model was published by Kang *et al.* (2010) describing an online information system for plant diseases based on weather data. This was developed for rice farmers in Gyeonggi-do in Korea, and is available at http://www.epilove.com. The information delivery system was based on a Linux server, using MySQL database, PHP and Java. Weather data are derived from a network of 82 synoptic and 627 automatic weather stations in Korea, collecting data at 1 h intervals. The input data are air temperature, RH and rainfall. The system generates hourly or daily warnings at the spatial resolution of 240 x 240 m. Interpolation of the weather data at this resolution was performed after evaluation. The leaf blast forecasting model was based on that of Yoshino (1979). Kang *et al.* (2010) concluded that the interpolation of rainfall and LW required improvement. They also highlighted that failure to estimate LW events based on the interpolated weather data was the main reason for low accuracy in the disease forecasting.

EPIRICE, a generic model for plant diseases, was developed by Savary *et al.* (2012) in Korea. This was coupled with GIS to map simulated potential epidemics of five major rice diseases globally, including leaf blast, brown spot, bacterial blight, sheath blight and rice turgo disease. The model used for the development of EPIRICE was based on that developed by Zadocks (1971), which forecast cereal rusts epidemics. The Zadocks model was modified by the addition of elements of plant growth, plant senescence and spatial disease aggregation. EPIRICE encompassed different hierarchy levels of a growing crop canopy, including disease sites on a leaf, whole leaves, tillers, plants, crop stands, world regions, and the world. The model was parameterized using reported data for each of the five diseases, and was combined with a few simplified growth stage characteristics. The model was linked to GIS, and crop establishment and daily historic climate data over a 2 year period. The data included temperature, precipitation, RH, dew point, solar radiation and wind speed. Other variables used were: sites, crop growth, epidemic onset, residence times, infection rate, age effect, temperature effect, wetness effect and aggregation. After the model's successful simulations of epidemics, the authors used the rice crop as a model system. They showed that the same model could be used at different levels of the crop hierarchy to simulate and map potential plant disease epidemics at the global level. They also suggested improvements in three specific areas: 1) the treatment of spatial structure of disease epidemics, 2) the handling of epidemiological processes in vector-borne diseases, and 3) the limited published disease progress curves and basic information.

In India, the Central Road Research Institute (CRRI) operated a simple leaf blast forecasting system based on empirical predisposed factors, which interacted with rice varieties. Seedling, rapid tillering after transplanting, and flower emergence were identified as the plant stages most susceptible to rice blast. It was also concluded that leaf age influenced the host susceptibility; plants with old leaves were less susceptible to blast than those with young leaves. The critical range of temperature for conidium penetration and infection was in the range of 25 to 26°C. Conidium germination appressorium formation occurred within 6–10 hours at 20–30°C in the presence of LW. The formation of dew, light rainfall or the occurrence of fog provided the necessary water required for germination of conidia. Analysis of the intensity of infection included records from experiments over several years. Infection had occurred under natural conditions when the minimum temperature during the night was 26°C and below, with the concomitant occurrence of 90% RH and greater. These conclusions were verified by experiments leading to the development of a forecasting system to assist rice farmers.

Kim *et al.* (2015), in Korea, published a novel model approach, which modified EPIRICE (Savary *et al.*, 2012). Their study involved two components: the modified EPIRICE and linkage to climatic change data, aiming to generate disease risk maps. Historical disease data and 1 km scale weather data were acquired for South Korea for 2002 to 2010. Additionally, the Yoshino model (1979) was used as a temperature effect module. Likely changes in the national disease probabilities were assessed under climatic change scenarios, to allow robust planning, while EPIRICE was calibrated and validated against the observed leaf blast incidence. They predicted daily climatic data based on the Intergovernmental Panel 4.5 on Climatic Change and Representative Concentration Pathways 8.5, while the outputs were displayed using GIS. The simulation predicted rice blast incidence epidemics until 2100. The authors concluded that likely magnitude of changes in disease risk in South Korea could be predicted. The model also estimated climate change impacts on crop losses from the disease and on disease control. Since this model was recently released, the authors suggested that more testing was required to validate the accuracy and integrity of the predictions.

Leaf and neck blast forecasting models

Japanese researchers were pioneers in the development of rice blast models due to the importance of the disease and the large quantities of agrochemicals used for the disease control in their country. Japan required elaborate forecasting to precisely determine the optimum time for applying fungicides to maximize profitable returns. The most original study on forecasting models was published by Kuribayashi and Ichikawa (1952). They studied the time relation between the number of conidia deposited on spore trap slides and severities of neck and nodal blast outbreaks for several rice varieties. An average of eight conidia was recorded for mild outbreaks, 24 for moderate outbreaks, and 175 for severe outbreaks. Many conidia were trapped in a region with severe blast outbreaks, while few or no conidia were trapped in a region with mild outbreaks. Data sets from 1934 to 1949 were used, and numbers of trapped conidia were correlated with blast severity for data derived from eight observatory stations at 5 d intervals. There were close correlations between conidium numbers and disease severity from July to September. It was concluded that spore trapping could provide reliable information for disease forecasting. Although questions were raised concerning calculations based on conidium trapping data at each station, combined data from eight stations could be used to forecast areas within a Nagano Prefecture. Similar forecasting attempts were made at many other prefectural experimental stations in Japan, and it was concluded that a developed formula for one region did not always fit another. This research was considered of great importance for Japanese rice growing. Many rice blast forecasting studies have since been published in Japan, based upon further knowledge of *P. oryzae*, the rice hosts and the environment.

Decade 1960

Ono (1965), also in Japan, developed a leaf and neck blast prediction model. This involved air-borne conidia in combination with sums of sunshine and a fertilizer index, using mean percent of sunshine, and temperature or precipitation, for forecasting leaf and neck blast outbreaks.

In India, Padmanabhan (1965) developed a model to formulate several forecasting rules. These were: 1) seedbed infection occurred when minimum temperature was 24 to 26°C for 4–7 d; 2) leaf blast occurred when minimum temperature was below 24°C for 4-5 days after transplanting and during tillering, and RH ≥ 90%; and 3) neck blast occurred when September-October conditions favoured leaf infection and temperatures were 20–24°C for a number of days coinciding with RH ≥ 90%. Severe leaf blast was necessary for neck blast occurrence.

Chiba *et al.* (1966) outlined a method for forecasting rice blast using field sheath inoculation. Variables of temperature, rainfall, sunlight and crop growth stage were correlated with disease severity, which was assessed each week by measuring the mycelium growth in rice sheath cells. A linear relationship was found between mycelium growth and disease severity, and a formula was proposed for the calculation of standard mycelium growth values. After testing predictions in the field, it was concluded that the standard value was related more to leaf blast than neck blast.

Suzuki (1969b, 1974) devised a rotary spore trap and determined that blast incidence was correlated with the number of spores collected. In earlier studies, Suzuki (1969c) found that when dry conidia ab-

sorbed water, they germinated within 2 h at temperatures above 16°C. The maximum number of conidia dispersed was detected in the middle of each night. Once conidia were discharged from conidiophores, they moved with the air flow. The number of conidia dispersing were indicated by an exponential formula, showing that the stronger the wind, the greater was conidium dispersal. For horizontal dispersion, the number of conidia dispersed in different wind velocities followed a log linear relationship with distance from an inoculum source. Almost all conidia were deposited near the source. Forecasting precision was improved by correcting for average wind velocity at the time of sampling.

Uehara (1985) in Japan used multivariate analysis techniques to classify regions according to occurrence of leaf blast in late July and neck blast from mid-September to early October. Seventeen years of data derived from 120 stations within paddy fields were used to correlate disease distribution with altitude. Leaf and panicle blast were shown to have similar distribution patterns, and panicle blast occurred in areas with mild leaf blast infections, when weather conditions were favourable after heading. This approach resembles the "pest zoning" concept proposed by Teng (1990).

Decade 1980

Uehara *et al.* (1988) tested BLASTAM (Koshimizu, 1983, 1988; Hayashi and Koshimizu, 1988) for forecasting leaf and panicle blast. Leaf blast occurrence was well-predicted, but not panicle blast. This indicated that hourly weather records should be used for disease forecasting. The model used daily weather data inputs supplied by AMeDAS. This system automatically recorded weather conditions, including wind direction and speed, types and amounts of precipitation, types and base heights of clouds, visibility, air temperature, humidity, sunshine duration and atmospheric pressure. BLASTAM could identify when and where favourable infection conditions occurred on a meso-scale. This extension service aimed to provide current and projected situations of local epidemics, and to recommend topical disease management advice for local rice growers. BLASTAM predictions were found to be reasonably accurate for leaf blast, but not panicle blast, so further improvements were needed. Although BLASTAM did not provide quantitative information on the disease progress besides predictions of disease outbreaks, it was useful in several prefectures of Japan. The theory was adopted that leaf blast epidemics start approx. 10 d after the first appearance of conditions favourable for infection. BLASTSAM predictions gave farmers enough time for disease management decision-making. Hourly weather recordings were also used as the basis for the forecasting. Nemoto and Ishiguro (2004) tested BLASTAM and BLASTL models (Hashimoto *et al.* 1982, 1984) in combination with AMeDAS, as a decision tool to identify rice blast favourable conditions in Japan. Their predictions were freely displayed on the Web.

The forecasting system of Ishiguro and Hashimoto (1988, 1989, 1991) and Ishiguro (1991) in Japan operated using stochastic functions to accurately predict leaf and panicle blast epidemics. In 17 cases, the leaf blast pathosystem was mostly described by deterministic equations generated from empirical data from previous laboratory and field studies. The framework of the model was very similar to BLASTL (Hashimoto *et al.*, 1982, 1984), except that the panicle blast model was stochastic, while BLASTL was a deterministic model. This stochastic panicle blast simulation model (PBLAST) used the Monte Carlo method (Hammersley and Handscombe, 1964); conidium deposition and penetration were treated as stochastic processes, and each panicle was subdivided into small infection site units. A probability function was used for conidium deposition, with consideration of wetness duration and wetness-temperature, and the probability of penetration of each deposited conidium into an infection site unit was computed. This pathogen penetration approach was similar to the Yoshino model. Rice heading, fertilization, grain growth, susceptibility of each infection site, appearance and growth of lesions, panicle blast severity and yield loss were calculated daily. Conidium formation, discharge, dispersal, deposition, and pathogen penetration and colonization were calculated every 3 h. AMeDAS weather data, additional wetness duration data, and data of host development, variety and cultivation practices, as well as number of conidia formed on leaf lesions, were used as model inputs. Validation results were inconsistent, while the model required a extensive computer resources. This model was a tool for epidemiological research rather than for practical disease forecasting. Furthermore, the model used some preliminary variables and functions that had not been experimentally verified.

Lee *et al.* (1989) in South Korea used spore traps to investigate blast outbreaks in experimental fields in Icheon and Suweon, to monitor leaf blast outbreaks. Primary meteorological variables included were temperature, RH, rainfall, sunshine hours and LW duration in the field. The number of conidia trapped in samplers was used to predict leaf blast severity and neck blast incidence. Differences in disease trends were found between the two sites and were attributed to differences in LW periods at each site. Differences were found for LW hours obtained by synoptic meteorological data and micro-meteorological data from within fields. These differences became greater for meteorological observatories distanced from the field. This model's approach was similar to Yoshino's (1979), but was highly dependent on data derived from specific locations.

Decade 1990

Empirical models to predict rice blast were developed by Calvero *et al.* (1994) and Calvero *et al.*, (1996a) in the Philippines, using regression equations generated from weather factors highly correlated with disease and the WINDOWS Pane program. Equations were used to predict rice blast on two cultivars cultivated at two testing sites, at Icheon in South Korea and at Cavite in the Philippines. This was an early effort to develop a model to forecast rice blast in two different countries. The input variables were: RH, precipitation (per day and total), mean, maximum and minimum temperatures, solar radiation and wind speed. Weather data acquisitions were from both sites but not from in-field collection points. The important role of saturated air for survival of airborne conidia to initiate infection was validated. However, the negative correlation of RH with neck blast was likely to be due to the lack of direct relationship between leaf and neck blast, because the two diseases require different weather conditions. Validations showed that all models developed for the two sites predicted blast reasonably well, with very few prediction errors. The only exception was for maximum lesion number and panicle blast incidence predicted at Icheon, and panicle blast severity on cultivar IR50 at Cavite. These models were shown to be useful for rice production systems, but further validation was suggested to improve prediction accuracy.

A procedure to assess temporal risk of rice blast was developed by Calvero *et al.* (1996b). This pat-terned the relationship between proneness to disease and time of sowing at three sites in the Philippines and Indonesia. The data were analyzed using multivariate statistical procedures. Historical meteorological data were used for the construction of the databases, including parameters of temperature, rainfall, RH, wind speed and solar radiation, and a single year weather database representative of the historical weather patterns. Using simulated weather avoided bias in selecting particular years at a particular site, because rice blast did not occur every year. Patterns were developed by combining predicted diseased leaf area and neck blast severity with hypothetical sowing dates, and they were grouped using cluster analysis. Differences in sowing dates fell into blast proneness groups, and these were difficult to identify from long-term weather patterns at the studied sites. Additionally, from discriminant analysis, various weather factors were shown to influence the classification of sowing dates into blast proneness groups. The discriminant empirical equations generated were therefore cultivar- and site-specific.

An information delivery system for the implementation of rice blast forecasting was developed in Korea by Park *et al.* (1998), based on real-time weather data. This system was composed of four Linux OS servers for: 1) the weather data management; 2) the database; 3) the program; and 4) a web server. The system collected hourly weather data through telephone modems from eight automatic weather stations installed in paddy fields in eight provincial rural development administrations. The input variables were: conidium release, solar radiation, wetness period, conidium deposition, air temperature, wind speed, infection, air temperature and rainfall. The program server ran the BLAST model to predict leaf blast severity (infected leaf area) and neck blast incidence. Accuracy of the forecasting information could be increased using weather data measured within rice paddy fields rather than that measured on macro or meso scales. This model might cause inaccurate forecasting due to its limited validity. Furthermore, the BLAST model had forecasting accuracy limitations especially when disease development was at low levels.

Decade 2000

Kapoor *et al.* (2004) reported a 50% reduction in rice blast in experimental plots managed using a

forecasting model developed for the Kangra district of Himachal Pradesh in India. Meteorological data were collected from farmer fields and experimental plots, while analyses of 13 years' data (1984–1996) was used to define critical periods of particular weather conditions, for comparisons with rice blast epidemics. In the 3 years of experimentation, optimum requirements for disease development during a crop season were: temperature 18–28°C and RH to remain greater than 90% for more than 9 h. Leaf blast rules for moderate to high severity were identified, along with neck blast predictions. Data on blast and on meteorological variables, including temperature, RH, rainfall, sunshine hours, wetness durations and wind velocity, were subjected to linear regression analysis. The requirements were RH greater than 80%, prevailing low temperature from 16-19°C with maximum limit of 28C°, 6–8 d of cloudy weather (low solar radiation) and 5–6 rainy days in 7 d. Further studies on rice blast and critical weather factors, such as LW period and distribution of rainfall, were required in the model to refine the predictions.

In Europe, development of rice blast forecasting models has been much less extensive than in Asia. Billoni *et al.* (2006) developed SIRBInt (Simulation of Rice-Blast Interaction), by monitoring airborne *P. oryzae* conidia with volumetric spore traps, and measuring temperature, RH, LW and rainfall. All input data were correlated to visual estimation of necrotic lesions on leaves, culms and panicle necks. The model consisted of Rice and Blast interacting sub-models. The Rice sub-model was derived from Oryza-1, while the Blast sub-model was newly developed. Oryza-1 was originally written in Fortran, and was modified for Italian rice characteristics and growing conditions. It was written for Visual Basic in an MS Excel environment, since it had already been used as the modelling environment in another study (Bocchi *et al.*, 1997). The model simulated rice blast interactions and development, including weather dependent crop and pathogen growth patterns. During four trial years the model simulated blast appearance in the field, and could be used as an advisory tool for fungicide applications. The SiRBint model consisted of many data, while the achieved approximation was not uniform. However, after an uncertainty analysis, it was shown that the more simulated processes were used within the model, the greater became the errors, since every simulation had its own uncertainty. The model could be improved with further

research to reduce the uncertainty risk, with more calibration and validation processes, and collecting data for more growing seasons. However, no further development of this model has been reported.

Mousanejad *et al.* (2009), developed a leaf blast and neck blast severity prediction model in Iran. This was based on data collected by weather stations 5 km from experimental rice paddies, and using simple spore traps in the Guilan province. The leaf and neck blast model was similar to that of Calvero *et al.* (1994). The collected weather data were: precipitation, daily minimum and maximum temperature, daily minimum and maximum RH and sunshine hours. Two quantitative models were developed for the prediction of leaf blast and neck blast indices. These parameters were also related to N fertilization and plant population density. Precipitation, RH, decreased temperature and sunny hours were shown to be the most important weather predictors for rice blast, since the correlations were high. Also, N fertilization was highly correlated with final leaf blast incidence. This research was a starting point for a comprehensive study on blast forecasting in Guilan province. The model is well-organized regarding input variables, but large distance of 5 km from experimental plots may have affected prediction accuracy.

Decade 2010

An early warning system for cool weather conditions was developed and operated by the Japan Meteorological Agency and the National Agriculture and Food Research/Tohoku Agricultural Research Center (Kanda, 2012). This was developed for the Tohoku District (Northern Japan). The model indicates high rice blast risk, as the disease is most serious when summer temperatures are low. The system estimates rice growth stage, abnormal weather damage, and occurrence of rice diseases, based on weekly weather forecasting data, and is presented on the Google Maps API. The current version provides 2-week temperature forecasts so farmers can make timely disease management decisions. Each user can choose an individual rice field. If a warning situation occurs, the users immediately receive notification by email or mobile phone, so control measures can be implemented before disease occurs. The system is available at http://www.reigai.affrc.go.jp.

Liang *et al.* (2013) developed a forecasting system that processed data collected from agricultural envi-

ronments through Wireless Sensor Network (WSN) technologies. The system aimed to provide a precise decision-making system for farmers. The sensor data stream was different from traditional streams characterized by real-time, sequential, missing data and lack of precision. The new system, used a sliding window to model the sensor data. Fuzzy rules were constructed based on expert knowledge, and fuzzy inference was used to collect different environmental data streams. This provided intelligent services to guide disease management or other applications. A simple disease outbreak prediction system was developed for rice blast, using Java and MATLAB. Environmental variables used for disease prediction, include temperatures for *P. oryzae* hyphal growth and conidium development, humidity and time. The fuzzy system gave probabilities of rice blast, classified into three risk levels, as 0-50% (low), 50-80% (moderate), and 80–100% (high). The models needed to enrich the database to make diagnoses versatile. The confidence factors of all the fuzzy rules and the each environmental variable affected the accuracy of the results. Increasing the number of environmental variables made definition of the rules very complicated, and the number of rules would increase exponentially.

In a more recent model approach in India, CLI-MARICE II was developed by Rafoss *et al.* (2013). This exploited the potential for climate adaptation and mitigation through online dissemination of pest and disease forecasts to rice farmers. The system was based on the reasoning that farmer's daily adaptation to the day-to-day variability in weather is a short-term analogy to the need for adaptation to long term climatic changes. Weather-driven mathematical models incorporating scientific insights on the biological responses of plant pests to climate were linked to automatic weather station networks, to provide pest risk forecasting/forewarning/early warning to rice farmers. The model used 224 automatic weather stations operated by the Tamil Nadu Agricultural Weather Network. The stations automatically transmitted weather variables implicated in the disease development process, including air temperature, wind speed, rainfall, solar radiation, soil temperature and moisture, LW and air humidity. The data were combined with disease epidemiology knowledge, and were formulated mathematically and stored in a MSQL database. The model followed rice blast, with assessments of leaf and neck blast used by Tamil Nadu Agricultural University (India).

No information was provided on the efficiency or current status of the model.

The most recently developed model was published in Italy by Bregaglio *et al.* (2016). The WARM model (Confalonieri *et. al.*, 2009) was used as a coupling generic model to simulate leaf and panicle blast impacts in a temperate climate. The hypothesis was that rice blast symptoms occurred in Northern Italy around the mid July. Weather and disease data derived from field trials under flooding irrigation were collected from 1996 to 2012. Variables used in the first coupling point were: air temperature, RH, LW, wind speed and precipitation. The simulation evaluated disease impacts on leaf area index and aboveground plant biomass. The second coupling point between the crop and the disease models reproduced the impacts of panicle blast on final yield by simulating reduced photosynthate accumulation in kernels. Good correlation between yield and disease assessments was achieved. This approach allowed exploration of blast-associated yield losses in relation to climate change or optimized fungicide strategies. The main limitations identified were: the lack of dedicated field experiments for collection of micro-meteorological data, the use of single values for the two blast symptoms and the lack of important pathogenesis information, including LW and conidium dispersal. Correcting these limitations would improve correlations, allowing the model to precisely predict real disease occurrence.

Neck blast models

A statistical method for forecasting neck blast was developed by Sasaki and Kato (1972), using data from 1962 to 1967. Cumulative numbers of diseased spikelets were plotted against time, forming sigmoid relationships for all cultivars grown under different conditions for all six years. Based on 112 sets of readings, each linear equation related the logit of the percentage of diseased spikelets 12 d after the crop stage of 50% heading and the rate of increase during the following 6 d. The numbers of diseased spikelets in the next 6 d were predicted by extrapolation. The regressions and correlations were shown to be valid only if the data were acquired during the same stage of development and within similar environmental conditions. Modifications were suggested to allow specific inhibitory or stimulatory effects on rates of infection development.

The first neck blast simulation model was developed by Takasaki (1982) in Japan. Conidium deposition and penetration were treated as stochastic processes, and individual panicles were treated as infection site units. Infection was computed according to a probability function, and affected panicles were classified into several types. The model's main limitation was that it did not account for secondary neck blast infections.

Rice blast forecasting models currently in use

Few rice blast forecasting models are currently in use for rice growers. Of the 52 published models, three operate inside the processes of other models or systems as modules or subroutines. These are those outlined by Yoshino (1979), Hashimoto *et al.* (1984) and Gunther (1986). Furthermore, four models are currently in use with the derived information available on the Web. Three of these were developed by Kaundal *et al.* (2006), Kang *et al.* (2010) and Kanda (2012). The fourth is currently available in Europe as a module implemented in the EU service "Monitoring Agricultural ResourceS" (MARS), operated by the Joint Research Center at Ispra (Italy). The system incorporates data from 1450 European weather stations and satellites. MARS issues bulletins on rice yield predictions every year, which include rice blast forecasting. Bulletins are available at http://mars.jrc.ec.europa.eu/mars. MARS uses the subsystem Water Accounting Rice Model (WARM) (Confalonieri *et al.*, 2010), which is an object-oriented simulation tool. The structure of WARM allows development of separate class modules for each aspect, and testing in an independent environment. Crop damage from rice blast is simulated within the processes, using variables of temperature, humidity and dew.

Examination of currently used rice blast forecasting systems has shown that they all require inputs from extended and systematic datasets, so that the forecasts cover large areas of rice cultivation. They require powerful computers, and advanced networks and servers with extensive database capabilities. Moreover, Yoshino's approach to LW operates through Kang *et al.* (2010) models, and the Japanese service based on Kanda's (2012) low temperature approach along with BLASTAM. The approach of Kaundal *et al.* (2006) to rainfall is closely connected to increased RH and moisture saturation, which

leads to elevated LW. The WARM model in MARS interpolates LW with a temperature and RH general approach, giving emphasis to *P. oryzae* penetration from germinating conidia.

Discussion

We have carried out an analysis of several factors to provide a deeper understanding of the model reviewed in the present study, to facilitate more accumulated knowledge, and to analyse information provided by each model.

Type of forecasting and input variables

Output type

The majority (60%) of the published rice blast models were developed to forecast leaf blast. This is the first symptom of *P. oryzae* infection that appears, so prediction of leaf blast is critical for early blast control, particularly in countries where the disease occurs early in the growing season. Just over a third (37%) of the blast models could forecast both leaf and neck blast. These models are likely to be more suitable for practical decision-making, since they can assist farmers throughout the crop growing period. In contrast, few of the models (4%) can forecast neck blast. Furthermore, neck blast prediction accuracy is reported to be low.

Input variables

The frequency of different input variables used in rice blast prediction models is presented in Figure 1. "Air Temperature" (67% of the models), "Relative Humidity" (58%) and "Rainfall" (56%) are the predominating weather variables used. Also, in more than the 30% of the models, variables regarding either *P. oryzae* or plant biology were included. These were "Spore Dissemination" (37% of the models), "Leaf Wetness (LW)" and "Plant Stage" (35%), "Sunlight" and "Wind Speed" (31%). Although variables such as "Air temperature", RH and conidium related inputs ("Spore Dissemination", "Spore Penetration", "Spore Disposition") are known to be critical factors affecting pathogenesis and disease development, these parameters have not been included in all models.

The infrequent integration of LW in the models (used in 35% of the models) may account for the general lack of prediction certainty, because LW is considered in the literature to be among the most

critical factors for the rice blast pathogenesis, and for connecting forecasting with rice canopy microclimate (Greer and Webster, 2001; Lanoiselet *et al.,* 2002; Yoshida *et al.,* 2015). Field measurements of LW require in-field devices, increasing the need of human interaction or automatic transmission systems. However, of the models with LW inputs, only 33% acquired real canopy data, and the others interpolated these parameters. Lanoiselet *et al.* (2002) suggested that data loggers should be placed in rice fields to assess microclimates of waterlogged fields to record realistic meteorological data needed to run the models. Significant differences occur between the RH values recorded outside field compared with those from rice canopies. Fluctuations in RH can reach an average of at least 20% greater inside canopies than above canopies or outside rice fields. Also, RH ≥ 95 %, equivalent to saturation, is assumed to indicate LW or moisture on leaf surfaces sufficient for sporulation and infection initiation on leaf tissues (Abrol, 2013). Trials carried out in three Mediterranean countries (Italy, Greece and Portugal) in 2015 and 2016 (RICE-GUARD FP7 project, unpublished data), where commercial mini-weather stations were installed inside rice paddies for monitoring canopy air temperature, RH and LW, allowed useful conclusions or hypothesis development relating to differ-

ent published results. For example, the high correlation of the LW with RH ≥ 95% reported by Albrol (2013) could not be validated as a narrow principal, because high LW values (> 65% coverage) occurred where RH was less than 95%, when rice blast risk could still be great. Nevertheless, interpolations with other variables may produce errors affecting the accuracy of the predictions. For example, linear regression analyses of variables "Air temperature" and RH, derived from these recent trials, resulted in R^2 values ranging from 0.203 to 0.683. Although adding more variables in the regression analyses, such as "Wind speed" and "Solar radiation", improved the R^2 values, but these were still not satisfactory, ranging from 0.750 to 0.762 (RICE-GUARD FP7 project, unpublished data). This level of relationship, although acceptable for field experiments, may still produce uncertainties in interpolations at a minimum of 24%. These findings agree with those of Kang *et al.* (2010), who concluded that inaccuracies in predictions from rice blast models are due to failures to interpolate LW with other weather variables.

Less frequently incorporated variables were "Spore release" (12% of the models), "Dew Point" (15%) and "Spore Penetration" (17%), while important parameters such as "Nitrogen Fertilization" and "Varieties" (host resistance) were infrequently used
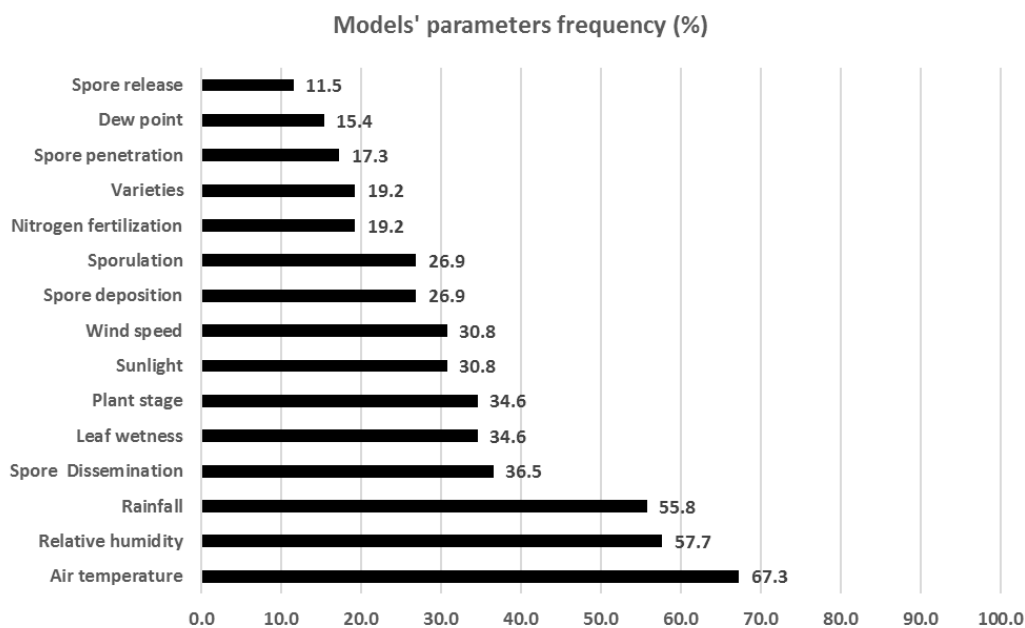
Models' parameters frequency (%)

Parameter	Frequency (%)
Spore release	11.5
Dew point	15.4
Spore penetration	17.3
Varieties	19.2
Nitrogen fertilization	19.2
Sporulation	26.9
Spore deposition	26.9
Wind speed	30.8
Sunlight	30.8
Plant stage	34.6
Leaf wetness	34.6
Spore Dissemination	36.5
Rainfall	55.8
Relative humidity	57.7
Air temperature	67.3

Figure 1. Frequency of different meteorological variables used in 52 rice blast forecasting models.
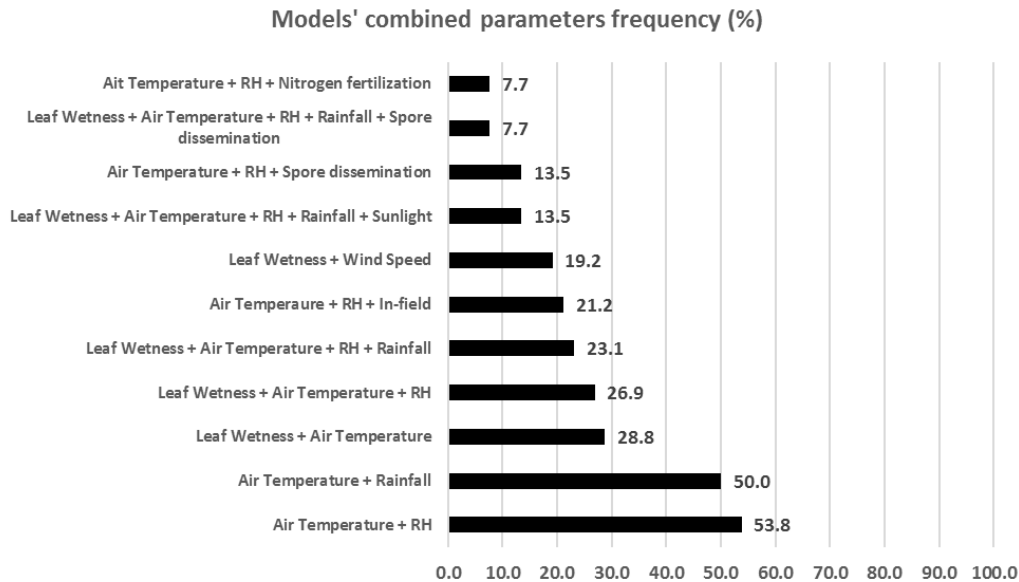
Figure 2. Frequency of combinations of meteorological variables used in 52 rice blast forecasting models (RH = Relative humidity).

(19% of models) (Ou, 1985; Freitas *et al.*, 2010). This limited integration could lead to anomalies, because both factors play important roles in *P. oryzae* pathogenesis and blast progress. For example, excessive nitrogen fertilization can increase disease severity by altering host susceptibility, even in highly resistant varieties. These varieties could escape disease even under favourable conditions for the pathogen, because of strong field resistance. The main reasons for limited integration of these variables may be that they require direct user interactions for inputs, or development of extended databases with frequent update requirements. However, recent technology improvements allow these features to be easily adopted, to improve future forecasting systems.

Input variable combinations

Combinations of variables were used in 54% of the models (Figure 2). "Air temperature + RH" and "Air temperature + Rainfall" were most commonly used (50%), followed by "LW + Air temperature" (29%) and "LW + Air temperature + RH" (27%). Less used combinations were "LW + Air temperature + RH + Rainfall" (23%) and "LW + Wind speed" (19%). Combinations with the least integration were "Air temperature + RH + Nitrogen fertilization" and "LW + Air temperature + RH + Rainfall + Spore dissemination" (7.7%).

Geographical distribution

The geographical distribution of the 52 forecasting models is presented in Figure 3. Most models originated from Japan (38%), while 13% came from Korea, 11% from India and 10% from the Philippines. Despite the magnitude of rice production in China, only 4% of the models originated from that country.

Timeline for model publication

The greatest numbers of model publications were from the 1980s (31%) or the 1990s (21%), Publications from the decades of 2000 and 2010 were less (15%), and frequency of publication since then remains at a stable rate. Introduction of advanced software engineering and new computer and sensor technologies has not recently increased the numbers of models developed, with relatively few models published after 2000.

Model modifications

In more than 30% of the publications, further revisions/development/modifications were suggested to be required by their authors to improve the efficiency and accuracy of disease predictions. Nevertheless, no evidence was presented for im-
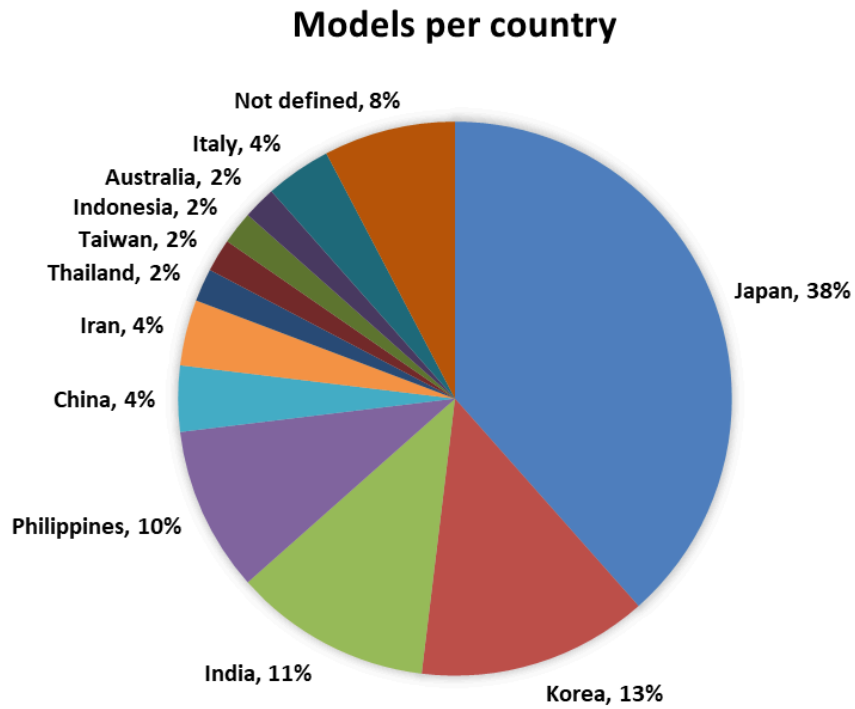
Models per country

Figure 3. Country distribution of published rice blast prediction models.
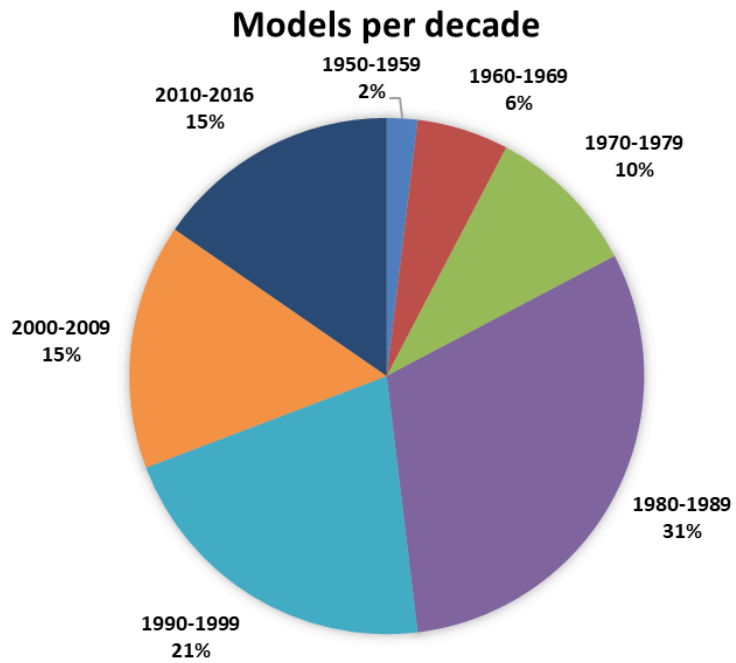
Models per decade

Figure 4. Publication date decades for rice blast prediction models.

plementing these improvements or that the models were further developed. Only four of the 52 models (8%) were modified after their original publication. These were: BLASTL (Hashimoto *et al.*, 1984), modified by Ashizawa *et al.* (2005); the model of Gunther (1986), modified by Tastra *et al.* (1987); BLASTSIM.2 (Calvero and Teng, 1991; 1992), modified by Luo *et al.* (1977); and EPIRICE (Savary *et al.*, 2012), modified by Kim *et al.* (2015).

Reference area

Most of the models, including those not based only on field data, reference areas were either small or limited, with reference to the magnitude of rice cultivation, the destructiveness of disease caused by *P. oryzae*, and the high annual crop losses. Even where an application or a tool is still in use, the forecasting is restricted to specific areas. There is also little or no evidence that the published models were evaluated or validated in geographical areas other than those where they were developed, including regions with similar environments. The only exceptions were: the model published by Luo *et al.* (1997), which was tested in five Asian countries; BLASTAM (Koshimizu, 1983; 1988; Uehara *et al.* 1988), tested in several prefectures of Japan; and BLASTSIM.2 (Calvero and Teng, 1991, 1992), which was refined and validated at IRRI in 1992.

Spatial distance scenarios

Reliability of forecasting type is affected by the source of weather data and whether data logging systems are located near or away from rice crops. Only 12 of the models (23%) used in-field weather data collection, and there is little evidence that this was from within rice canopies. Park *et al.* (1998) concluded that the absence of rice crop microclimatic conditions could lead to unreliable model predictions. Moreover, some theoretical approaches have developed forecasting models that are based only on historic data derived from study areas or countries.

Recommendations

Future attempts to develop rice blast prediction systems should consider the recommendations outlined below. The integrity of weather data collected from different points (in-field, outside the field or large distances from rice fields) should also be considered.

1) Model integration of modules or routines with two-way interactions should be used, giving the ability for end-users to input or parametrize variables. These can affect rice blast incidence or severity, and could include sowing dates, variety resistance and rates of nitrogen fertilization.
2) Canopy recordings should be made of the most critical variables (e.g. LW, air temperature and RH).
3) LW interpolation errors can be reduced by adding variables that can greatly affect dryness (wind speed and solar radiation). Interpolation of LW should be eliminated.
4) The number of data collection points should be large, utilizing and integrating modern technologies (smartphones, GSM networks) for in-field recording and data transmission.
5) Conidium trapping methods, which require specialized in-field expertise, should not considered to be an essential model component. Automatic systems should be used to improve widespread monitoring of rice cultivation areas.

Conclusions

Analysis of published rice blast prediction models has provided comprehensive knowledge on rice blast forecasting. Weather variables, such as "Air temperature", "Relative Humidity", "Spore Dissemination" and "Leaf Wetness" are among the most critical model inputs, since these play important roles in *P. oryzae* pathogenesis and rice blast development. However, the present review has shown that most studies have not included the combinations of inputs of these variables. Nevertheless, interpolations were often attempted, to calculate weather variables, an approach likely to lead to uncertainties. Difficulties in retrieving canopy monitored microclimate data is another limitation. In-field conditions differ substantially compared with the parameters recorded in weather stations located above, or well-separated from, rice crops or cultivation areas.

This review has also shown that very few published rice blast prediction models can be used for long periods (years) or in different geographical regions. Study of errors, uncertainties, improvements and modifications will assist development of more reliable forecasting systems. New remote sensing

technological innovations will assist canopy data collection.

The contributions of information derived from rice blast prediction models towards improvement of disease management has been limited through the decades. Prediction of initial *P. oryzae* infection and the patterns of rice blast development are the most important factors for forecasting this disease. Despite the development of 52 published rice blast prediction models in the last 67 years, the majority of these are research oriented. The question of Gold (1988) is still very relevant: "How useful is the information provided by the model relative to its intended purpose?"

Acknowledgments

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