24. Kakade, S. B. and Dugam, S. S., Impact of cross-equatorial flow on intra-seasonal variability of Indian summer monsoon rainfall. *Geophys. Res. Lett.*, 2008, **35**, L12805.
25. Dee, D. P. *et al.*, The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q. J. R. Meteorol. Soc.*, 2011, **137**, 553–597.
26. Rajeevan, M., Bhate, J., Kale, J. D. and Lal, B., High resolution daily gridded rainfall data for the Indian region: analysis of break and active monsoon spells. *Curr. Sci.*, 2006, **91**, 296–306.
27. Shepard, D., A two-dimensional interpolation function for irregularly-spaced data. In Proceedings of the 23rd ACM National Conference, ACM, January 1968, pp. 517–524.
28. Fasullo, J., Atmospheric hydrology of the anomalous 2002 Indian summer monsoon. *Monthly Weather Rev.*, 2005, **133**(10), 2996–3014.
29. Gadgil, S. and Joseph, P. V., On breaks of the Indian monsoon. *Proc. Indian Acad. Sci.* (*Earth Planet. Sci.*), 2003, **112**, 529–558.
30. Terray, P., Delecluse, P., Labattu, S. and Terray, L., Sea surface temperature associations with the late Indian summer monsoon. *Climate Dyn.*, 2003, **21**, 593–618; doi:10.1007/s00382-003-0354-0.
31. Park, H.-S., Chiang, J. C. H., Lintner, B. R. and Zhang, G. J., The Delayed effect of major El Niño events on Indian monsoon rainfall. *J. Climate*, 2010, **23**, 932–946; doi:10.1175/2009jcli2916.1.

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A weather-based forecast model for capsule rot of small cardamom

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Small cardamom is an economically important spice crop. However, cardamom is susceptible to several diseases that significantly reduce yield. Proactive prevention of these diseases based on advance warning can enhance the efficiency of disease control and reduce environmental load of pesticides. Many of these diseases are governed by weather variables (for example, through control of fungal growth). This work presents a disease (capsule rot of cardamom) forecast model based on a set of meteorological variables. While no single weather variable provides successful simulation, an optimal combination of weather variables provides sufficient skill for advance warning of the disease.

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Keywords: Capsule rot disease, forecasting, meteorological variables, small cardamom.

SMALL cardamom (*Elettaria cardamomum* L. Maton) is an economically important spice crop. The current global demand for cardamom is 40,000 tonnes annually and is expected to grow. India is a major exporter of cardamom, with a significant number of farmers dependent on it. The Cardamom Hills Reserve (CHR) in Idukki district of Kerala is a major source of this spice. The cool, humid condition prevailing in cardamom ecosystem makes the plants susceptible to several diseases. These lead to significant crop loss that adversely affects the livelihood of the farmers and the national economy in general.

Capsule rot, popularly known as *Azhukal* disease, is the most serious disease of cardamom. It was reported for the first time from plantations of Idukki district, Kerala[1]. The disease is caused by the fungal pathogen *Phytopthora meadii* MC Rae of A2 mating type[2]. It is a major problem affecting cardamom cultivation in Idukki and Waynaad districts of Kerala and Anamalai hills in Tamil Nadu[3]. The disease generally makes its appearance after the onset of the southwest monsoon. Disease symptoms develop mainly on the capsules, young leaves, panicles and tender shoots as water-soaked lesions. During favourable climatic conditions, the size of lesions enlarges and in extreme cases the whole panicle or the whole psuedostem decays completely. In such cases the rotting extends to underground rhizomes as well. The root system of such plants becomes decayed and the entire plant collapses. Crop loss can be 100% in severely disease-affected plantations.

It had been noticed in case of epidemiology of *Azhukal* disease that high disease incidence is correlated with high and persistent rainfall during the monsoon season[4]. The number of *Phytophthora* propagules increases in the soil and results in heavy disease incidence coinciding with high soil moisture levels (34.3–37.6%), low temperatures (20.4–21.3°C), high relative humidity (83–90.6%) and high rainfall (320–400 mm) during June to August[5]. Several studies have highlighted the special environmental and climatological features of the CHR, such as long-period (centennial) rainfall[6,7] and the physiological ecology of cardamom[8]. Similarly, there have been studies on the characteristics of *Phytophtora* inoculum in CHR soils[9]. Due to the dependence of disease severity (fungal growth) on weather variables, the production and sustainability of cardamom are vulnerable to changes in the regional climate[10]. However, these analyses have not yet resulted in developing a mathematical model to predict the disease.

Table 1. Weather variables and their correlation coefficients with disease occurrence (monthly values over a year); values above 95% significance are marked with *. Maximum significance level is 99.92 and minimum significance level is 0.20

Meteorological variable	Period of availability of data	Correlation coefficient with disease occurrence 2008	2010	Average
Rainfall (total mm)	2000–2010	0.85*	0.65*	0.82*
Morning humidity	2000–2010	0.84*	0.61*	0.81*
Rainy days	2008 & 2010	0.73*	0.63*	0.74*
Afternoon humidity	2008 & 2010	0.73*	0.63*	0.69*
Sunshine	2000–2010	–0.60*	–0.60*	–0.63*
Afternoon soil temperature (5 cm)	2008 & 2010	–0.64*	–0.47*	–0.57*
Evaporation	2008 & 2010	–0.59*	–0.36	–0.59*
Afternoon soil temperature (10 cm)	2000–2010	–0.53*	–0.42	–0.51
Afternoon soil temperature (20 cm)	2000–2010	–0.60*	0.12	0.00
Wind	2008 & 2010	0.17	0.32	0.27
Maximum temperature	2000–2010	–0.26	–0.18	–0.19
Morning soil temperature (10 cm)	2008 & 2010	–0.11	–0.31	–0.22
Morning soil temperature (20 cm)	2008 & 2010	–0.21	0.18	0.13
Morning soil temperature (5 cm)	2008 & 2010	–0.01	–0.22	–0.10
Minimum temperature	2000–2010	–0.11	0.05	–0.04

Table 2. Performance parameters of cardamom simulation model

Parameter	Coefficient	Standard Value, Year: 2008 & 2010	2001–2007 & 2009	Range
Rain	α_{R_f}	0.100	0.100	0.1–1.0
Morning humidity	$\alpha_{R_{HM}}$	0.295	0.295	0.1–1.0
Afternoon humidity	$\alpha_{R_{HA}}$	0.295	–	0.1–0.5
Afternoon soil temperature (5 cm depth)	α_{T_A}	1.618	1.141	1.0–2.0
Sunshine	α_S	0.790	2.01	0.1–5.0
Evaporation	α_E	0.839	–	0.1–1.0

In addition to its immediate predictive value, a weather-driven model provides a natural candidate for investigating the impact of climate change on cardamom. The potential of disease prediction model to minimize loss has been recognized; however, most of the earlier workers on disease prediction have utilized regression models (both linear and nonlinear) to develop forewarning models of different pests[11–14]. Several other works have also explored application of forecast models for plant diseases like onion botrytis[15] and *Alternaria solani* on tomato[16]. Other approaches, such as neural network-based forecasting[17] have been explored for plant diseases. For example, Chakraborty *et al.*[18] utilized neural network technique for predicting severity of anthracnose diseases in legume crop. However, these methods have their inherent weaknesses; in particular, the question of data optimality also applies to neural networks.

An optimal set of variables needs to be identified, as weather and environmental variables (like cloud cover and radiation) are not all mutually independent. One approach to study disease occurrence is to develop detailed understanding of the pathology and biological processes involved in the disease and design mitigative strategies. The other approach is to identify causative associations between disease and other external variables for warning and proactive mitigation; the second approach is followed here one. However, these studies did not provide quantitative functional relationships between weather variables and disease occurrence for developing dynamical forecast model. Relation between weather variables and characteristics of certain diseases like periodicity of airborne spores of *Alternaria dauci* was noted in some early studies[19]. However, attempts to use weather variables for predictive use are still rare, although growing in number[20]. In this study, we analysed the interaction of various weather variables and cardamom capsule rot incidence to develop a calibrated functional forecast model.

The analysis and methodology are based on daily data on meteorological variables and disease occurrence over CHR (Tables 1 and 2). Observations were made at the Research Farm of Indian Cardamom Research Institute (ICRI), Myladumpara, and Idukki district. The meteorological parameters like maximum and minimum temperature (°C), soil temperature (°C) at 5, 10, 20 cm depth of the soil, relative humidity (%), wind velocity (km/h), sunshine (h), rainfall (mm), number of rainy days and evaporation (mm) were recorded at the Agromet station in the ICRI campus, which is located at an altitude of 1050 m above msl. The weekly average of each meteorological parameter is represented. While seven meteorological variables (Table 1) were available and four were used for the period 2000–2007 and 2009, a set of additional two variables was used for the years 2008 and 2010 to construct the prediction model.

The incidence of capsule rot was recorded by counting the number of infected capsules against healthy ones among five infected panicles selected randomly, as described by Thomas *et al.*[21]. The disease incidence (%) was monitored every month.

Out of the 15 variables (Table 1), an optimal set of weather variables was first determined through an analysis of correlation between the annual cycles (12 months) of a weather variable and disease occurrence. Based on this analysis as well as conceptual argument on likely independence of these variables, six weather variables were identified to construct the optimal set for developing the disease prediction equation

$$D(m) = (\alpha_{R_f} \times R_f) + (\alpha_{R_{HM}} \times R_{HM}) + (\alpha_{R_{HA}} \times R_{HA}) - (\alpha_{T_A} \times T_A) - (\alpha_S \times S) - (\alpha_E \times E),$$

where $D(m)$ is the disease incidence (%); R_f, rainfall; R_{HM}, morning humidity; R_{HA}, afternoon humidity; T_A, afternoon soil temperature (5 cm depth); S, sunshine; E, evaporation; α_n, coefficients.

The coefficients describe (Table 2) the strengths of contribution of the meteorological variable concerned and to begin with do not have precisely defined values. A process of calibration, through minimization of average error between forecasts and observation, was followed to determine the optimum value of a parameter. The coefficients that produced best fit were then adopted (Table 1). In what follows, we shall first analyse the results for 2008 and 2010 for which the complete set of 15 meteorological variables was available. We shall then consider the prediction skill with the limited set of six meteorological variables to examine the issue of data optimality. The overall organization of the forecast system is schematically presented in Figure 1.

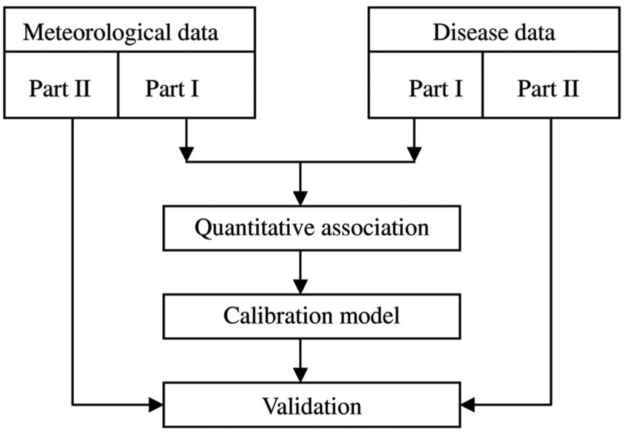

Figure 1. A schematic representation of the weather-based forecast model.

The importance of cardamom for the Indian farmers can be appreciated from the strong positive trend that prevails since 1950 (Figure 2 *a*); from a mere 3000 tonnes around 1960, the cardamom production in India now is about 18,000 tonnes. A major part of this production takes place over the CHR region. However, cardamom production exhibits strong inter-annual variability that has significant correlation with rainfall averaged over Kerala but not with all-India rainfall, as expected (Figure 2 *b* and Table 3). However, disease incidences are controlled by local conditions and need to be related in a prediction model.

The annual cycles of the meteorological variables and disease occurrence for the two years show significant differences (Figure 3). Thus any functional relation between disease occurrence and the weather variables should be able to explain this variability. Indeed, functional forecast model based only on any of the meteorological variables

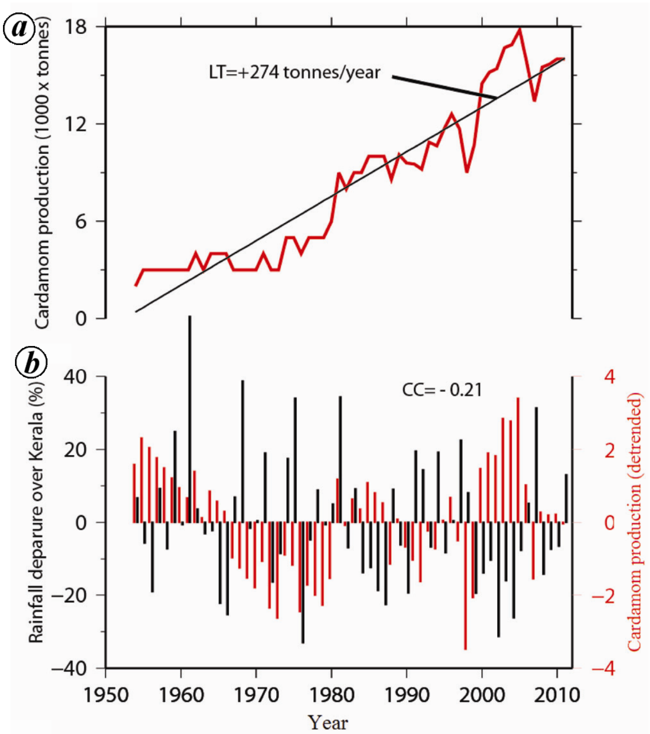

Figure 2. ***a***, Year-to-year variation (red line) in annual production of cardamom over India for the period 1954–2011 shown along with its linear trend line (black). The annual production data is from Indiastat. ***b***, Percentage departure (black line) of seasonal (June–September) rainfall over Kerala and detrended cardamom production (red line). The rainfall data is from IITM.

Table 3. Correlation coefficient between seasonal (June–September) rainfall and annual cardamom production

Parameter	All-India rainfall	Rainfall over Kerala
Cardamom production	–0.25	–0.22
Cardamom production detrended	–0.02	–0.21

like afternoon soil temperature, morning humidity, daily rainfall or sunshine shows limited skill for either 2008 or 2010 (Figure 4, left and right panels respectively).

In contrast, forecasts generated with the functional forecast model with the calibrated configuration (Table 2), show significant skill for both 2008 (Figure 5 *a*) and 2010 (Figure 5 *b*); the average forecast is also well correlated with the observed disease severity and annual cycle (Figure 5 *c*). In particular, the observed absence of disease incidence until about June is well captured in the functional forecast model, while it is a major error in forecasts with any single variable (Figure 4). However, the disease occurrence in the post-monsoon season decreases less rapidly in the forecasts than in the observation (Figure 5).

The result, however, also shows that there are cases of unsystematic overprediction of disease incidences in the post-monsoon season. It needs to be emphasized that the forecast model is not perfect, and some forecast errors will always remain. However, in the present case, a source of error that can be reduced through proper observations is the accuracy of the ranges of the meteorological variables adopted to represent disease conditions. In particular, the semi-empirical values of thresholds and cut-offs need to be determined in a more rigorous and precise manner. Besides, persistence of meteorological conditions (that may not prevail in winter) may need to be considered to avoid false warnings in the post-monsoon period.

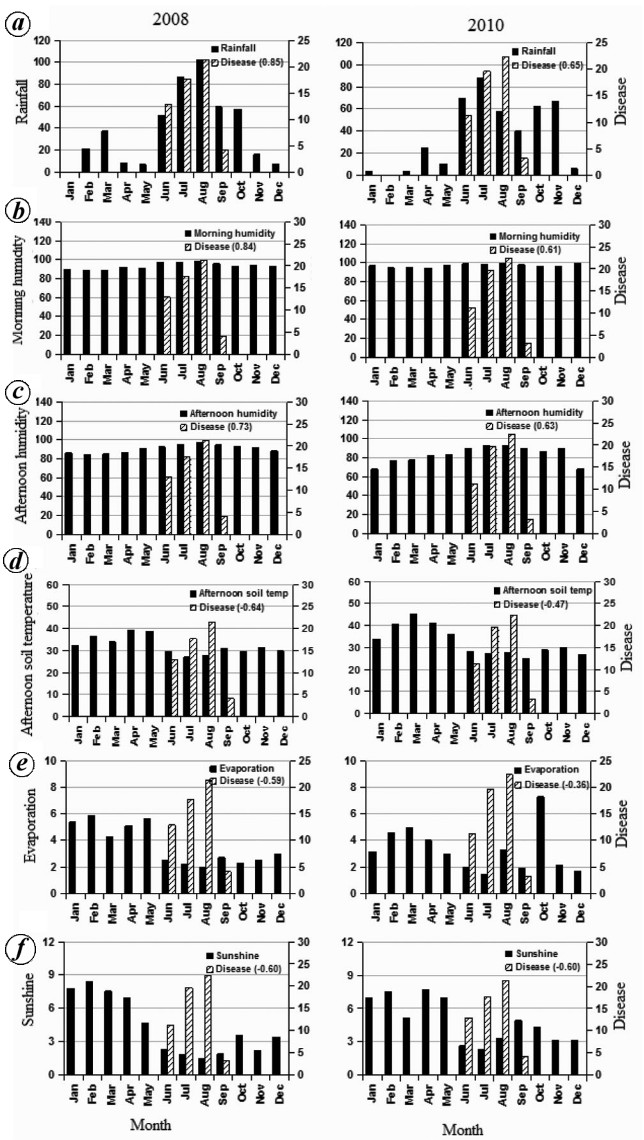

Figure 3. Annual cycles of disease occurrence and meteorological variables for (left panel) 2008 and (right panel) 2010. (***a***) Rainfall; (***b***) Morning humidity; (***c***) Afternoon humidity; (***d***) Afternoon soil temperature (at 5 cm depth); (***e***) Evaporation and (***f***) Sunshine.

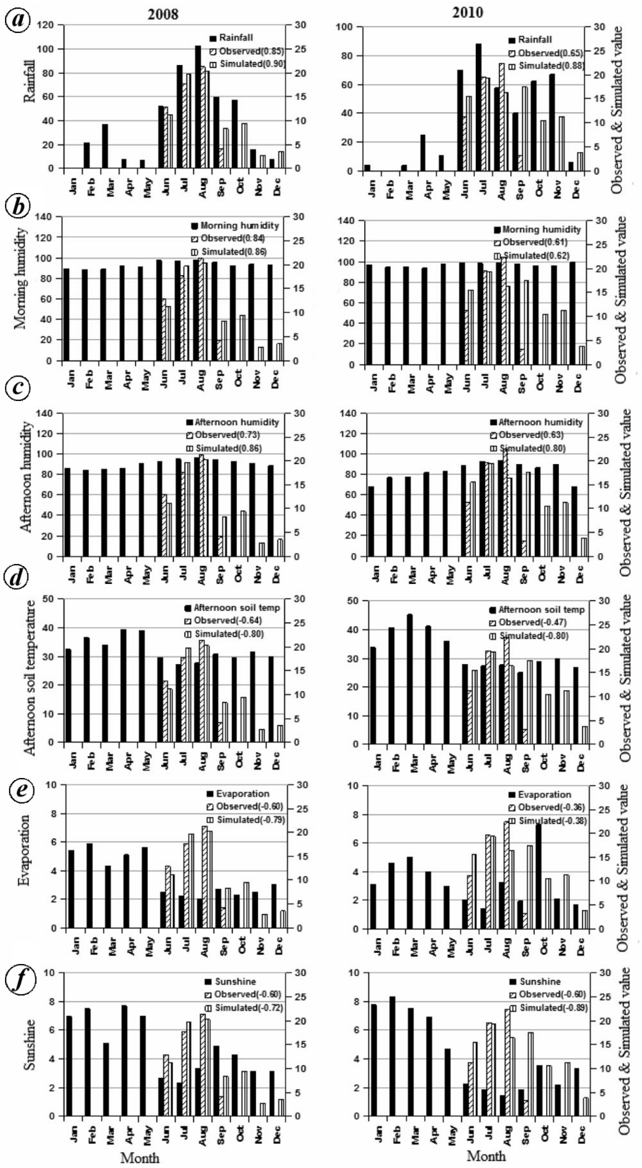

Figure 4. Observed and simulated values of disease occurrence with (***a***) Rainfall; (***b***) Morning humidity; (***c***) Afternoon humidity; (***d***) Afternoon soil temperature (at 5 cm depth); (***e***) Evaporation and (***f***) Sunshine for 2008 (left panel) and 2010 (right panel).

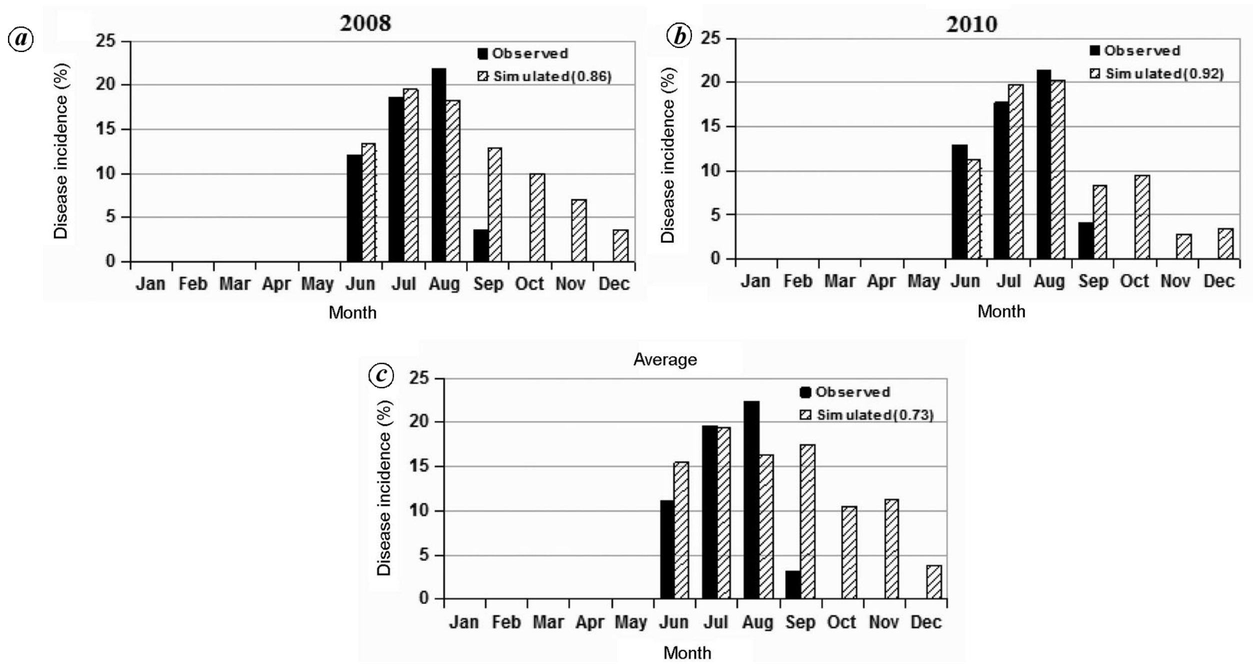

Figure 5. Observed and simulated values of disease occurrence with the forecast model for (***a***) 2008, (***b***) 2010 and (***c***) average.

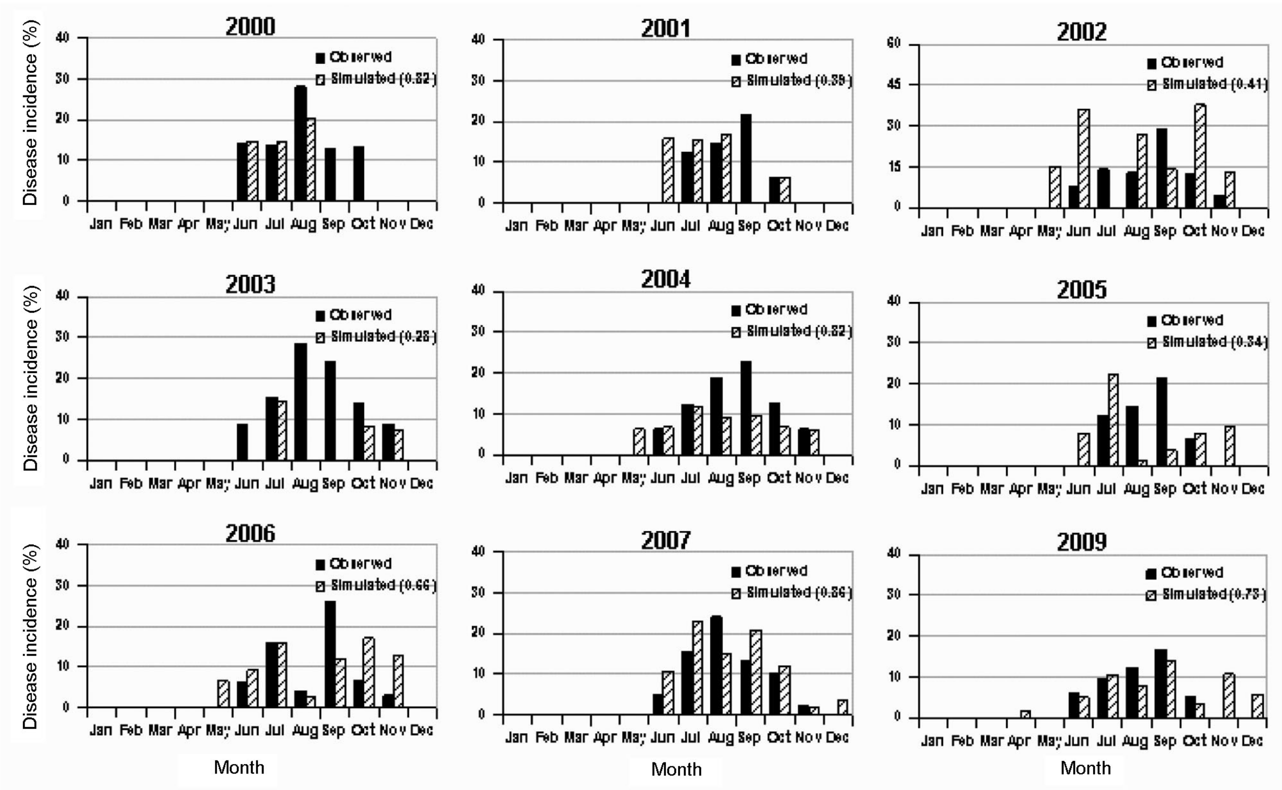

Figure 6. Comparison of observed and simulated disease load of capsule root of cardamom with simulation carried out with only four meteorological variables (rainfall, humidity, afternoon soil temperature (5 cm depth) and sunshine) for 9 years. Numbers in brackets represent the correlation.

Forecasts with a smaller set of meteorological variables also show only limited skill for most of the years (2000–2007 and 2009; Figure 6). Not only is the correlation coefficient between observed and predicted disease loads low, the simulated annual cycle also poorly fits the observed cycle. The importance of optimality of the set of meteorological variables for disease prediction is further highlighted by correlation coefficient between observed

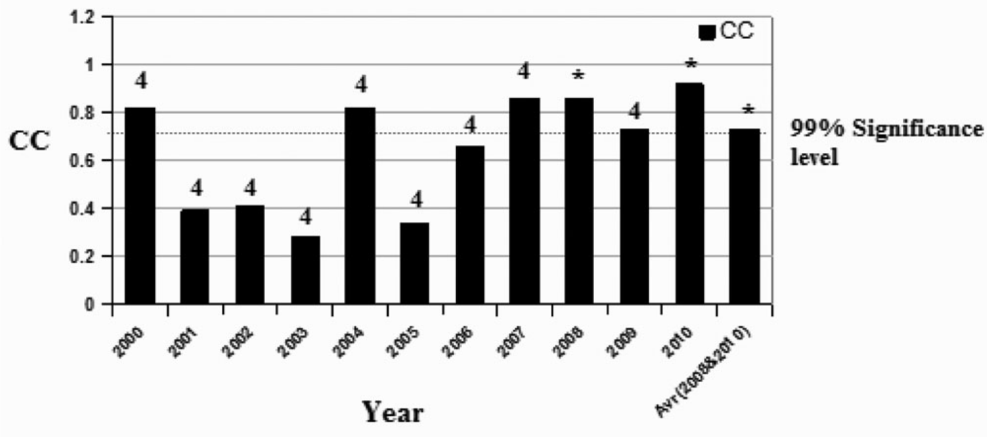

Figure 7. Correlation coefficients between observed and simulated disease load for 11 years (2000–2010) and average of 2008 and 2010. The * marked cases are with six meteorological variables and others are with four variables. The horizontal dashed line represents the 99% significance level.

and simulated disease load for the years 2000–2007 and 2009 (Figure 7). Both the years (2008, 2010) with prediction based on six atmospheric variables have correlation coefficient significant at 99% level of significance; on the other hand, the years with prediction based on only four meteorological variables are generally characterized by low correlation coefficient (Figure 7).

Unlike in the present case of capsule rot, the challenge is likely to be greater for time-discontinuous processes. However, approach similar to the one adopted here can also be applied to time-discontinuous disease incidence if the sample size is sufficiently large. For example, if the disease incidences and the meteorological variables are recorded at high frequency but over (short) discontinuous intervals, then the method can be applied to create piecewise continuous data. Similarly, inclusion of time lag between the meteorological variables and disease incidence is methodologically possible and may improve forecast skill; however, this requires observations of both meteorological and disease conditions at high temporal resolutions.

A forecast model of capsule rot of cardamom based on an optimal combination of weather variables provides sufficient skill. Also, the skill is not dependent on precise values of the model parameters, indicating the robustness of the model. However, appropriately designed observation system for an optimal set of meteorological variables, is necessary to achieve improved and useful forecast skill. These results can be integrated to atmospheric (meso-scale) forecasts to drive the disease forecast models to issue warning and alerts. The methodology is generic, and can be applied over different regions with necessary calibration.

1. Menon, M. R., Sajoo, B. V., Ramakrishnan, C. K. and Remadevi, L. A., New *Phytophthora* disease of cardamom. *Agric. Res. J. Kerala*, 1972, **11**, 93–94.
2. Suseela Bhai, R. and Sarma, Y. R., Characterization of *Phytophthora de Bary* inciting capsule rot/*Azhukal* and leaf blight disease of cardamom (*Elettaria cardamomum* L. Maton). *J. Plantation Crops*, 2005, **33**, 193–203.
3. Thomas, J., Suseela Bhai, R. and Naidu, R., Comparative efficacy of fungicides against *Phytophthora* rot of small cardamom. *Pesticides* (*Fungicide Special*), 1989, **23**(9), 40–42.
4. Nair, R. R., Investigations of fungal diseases of cardamom. Ph D thesis, Kerala Agricultural University, Trissur, p. 161.
5. Nair, R. R. and Menon, M. R., *Azhukal* disease of cardamom. In *Proceedings of the Workshop on Phytophthora Diseases of Tropical Cultivated Plants* (ed. Nambiar, K. K. N.), CPCRI, Kasaragod, pp. 24–33.
6. Murugan, M., Mukund, V., Ramesh, R., Hiremath, M. B., Josephraj Kumar, A. and Shetty, P. K., Centennial rainfall variation in semi arid and tropical humid environments in the cardamom hill slopes, southern Western Ghats, India. *Caspian J. Environ. Sci.*, 2008, **6**(1), 31–39.
7. Gopakumar, C. S., Impacts of climate variability on agriculture in Kerala. Thesis, Cochin University of Science and Technology, 2011.
8. Murugan, M., Shetty, P. K., Ravi, R. and Subbiah, A., The physiological ecology of cardamom (*Elettaria cardamomum* M) in cardamom agroforestry system. *Int. J. Environ. Res.*, 2009, **3**(1), 35–44.
9. Bhai, R. S. and Sarma, Y. R., Spatial distribution of *Phytophtora* inoculum in cardamom soils. *Indian Phytopathol.*, 2008, **61**(1), 95–98.
10. Murugan, M., Shetty, P. K., Anandhi, A. and Ravi, R., Present and future climate change in Indian Cardamom Hills: implications for cardamom production and sustainability. *Br. J. Environment Climate Change*, 2012, **2**(4), 368–390.
11. Agrawal, R., Mehta, S. C., Kumar, A. and Bhar, L. M., Development of weather-based forewarning system for crop pests and diseases – Report from Indian Agricultural Statistics Research Institute, Central Research Institute for Dryland Agriculture, Hyderabad, 2004.
12. Desai, A. G. *et al.*, *Brassica juncea* powdery mildew epidemiology and weather-based forecasting models for India – a case study. *J. Plant Dis. Protect.*, 2004, **111**(5), 429–438.
13. Chattopadhyay, C. *et al.*, Forecasting of *Lipaphis erysimi* on oilseed Brassicas in India – a case study. *Crop Protect.*, 2005, **24**, 1042–1053.
14. Chattopadhyay, C. *et al.*, Epidemiology and forecasting of *Alternaria* blight of oilseed *Brassica* in India – a case study. *J. Plant Dis. Protect.*, 2005, **12**(4), 351–360.

15. Vincelli, P. C. and Lorbeer, J. W., Forecasting spore episodes of *Botrytis squamosa* in commercial onion fields in New York. *Phytopathology*, 1988, **78**, 966–970.
16. Madden, L., Pennypacker, S. P. and Machnaa, A. A., FAST, a forecast system for *Alternaria solani* on tomato. *Phytopathology*, 1978, **68**, 1354–1358.
17. Dewolf, E. D. and Francl, L. J., Neural network classification of tan spot and stagonespore blotch infection period in wheat field environment. *Phytopathalogy*, 2000, **20**(2), 108–113.
18. Chakraborty, S., Ghosh, R., Ghosh, M., Fernandes, C. D. and Charchar, M. J., Weather-based prediction of anthracnose severity using artificial neural network models. *Plant Pathol.*, 2004, **53**, 375–386.
19. Langenberg, W. J., Sutton, J. C. and Gillespie, T. J., Relation of weather variables and periodicities of airborne spores of *Alternaria dauci*. *Phytopathology*, 1977, **67**, 879–883.
20. Hooker, D. C., Schaafsma, A. W. and Tamburic-Ilincic, L., Using weather variables pre- and post-heading to predict deoxynivalenol content in winter wheat. *Plant Dis*., 2002, **86**, 611–619.
21. Thomas, J., Susela Bhai, R. and Naidu, R., Capsule rot disease of cardamom (*Elettaria Cardamomum* Maton) and its control. *J. Plantation Crops (Suppl.)*, 1991, **18**, 264–268.

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Is primary productivity in the Indian Ocean sector of Southern Ocean affected by pigment packaging effect?

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The probable cause for photoinhibition of primary productivity (PP) in the surface layers of the Indian Ocean sector of the Southern Ocean (SO) was studied during the austral summer (February) 2010. Chlorophyll *a* (Chl *a*) and PP values were higher for polar stations compared to offshore stations and showed surface maxima; however, subsurface Chl *a* maxima was observed in two of the offshore stations. Biomass explained 36% of variance in PP and was not the sole controlling factor for PP variability. Euphotic zone integrated PP showed increasing trend from offshore to polar stations and varied from 159.56 to 1083.57 mg C m^{-2} d^{-1}. The relationship between Chl *a*-specific PP (P^B) and the corresponding photosynthetically active radiation in the water column was linear for offshore and curvilinear for polar stations, indicating the occurrence of 'photoinhibition' in the surface waters of polar stations. This could be ascribed to the onset of pigment packaging (the 'package effect') as larger phytoplankton (diatoms) dominated the polar stations, where macronutrients ratio was ideal (N : P ~ 16 and N : Si ~ 1) for growth of diatoms. Despite high Chl *a* in the polar waters, the corresponding PP was proportionally not high compared to the offshore stations. We suggest that larger phytoplankton are susceptible to pigment packaging, which in turn decreases their light-absorption/photosynthetic efficiency, resulting in lower PP, which is otherwise expected to be higher in the presence of elevated biomass.

Keywords: Light absorption, package effect, primary productivity, phytoplankton community.

THE Southern Ocean (SO) is potentially one of the most productive regions in the World's Oceans, considering the concentration of macronutrients (especially NO_3) it retains in the surface layers. Nevertheless, it is characterized by low primary productivity (PP) or high-nutrient low-chlorophyll (HNLC) phenomenon. The candidate mechanisms suggested to control the magnitude of PP in this HNLC ecosystem include fluctuating light levels, low iron supply, silicic acid concentration, high grazing pressure and low water temperature[1]. PP plays a significant role in drawdown of atmospheric CO_2 and transports it to the ocean interior through 'biological pump'. Thus, it is imperative to have a clear understanding of the cause(s) responsible for PP variability in the SO. PP in nutrient-rich waters is a function of three basic variables: chlorophyll *a* (Chl *a*), photosynthetically active radiation (PAR) availability, and light absorption capacity (Chl *a*-specific absorption coefficient)[2]. Beside this, PP also depends on another photo-physiological property of the phytoplankton, the efficiency with which the microscopic plants are able to convert the absorbed PAR into carbon (i.e. the quantum yield of carbon fixation). The light absorption capacity and the quantum yield of carbon fixation have been reported to be dependent on the phytoplankton community composition[3,4]. The light-absorbing efficiencies of phytoplankton communities directly regulate PP and are the major biological determinant of *in situ* subsurface light field in case I waters[5,6].

In oceanic environment, shifts in the hydrological parameters drive the changes in phytoplankton composition and their mean cell size[7,8], and hence, influence the internal accumulation of pigments and their packaging degree[9,10]. Thus, hydrological alterations affect the light-absorption/photosynthetic efficiency of phytoplankton communities. The 'package effect' (i.e. loss of linearity between light-harvesting efficiency and pigment packaging) originates from intracellular shading of the chloroplasts

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