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Lead paper

Crop simulation models as tools for agro-advisories for weather and disease effects on production

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ABSTRACT

Seasonal and daily variations in weather are major determinants of cropping practices, crop yield, diseases, and crop quality. Crop simulation models have capabilities to predict crop growth response to weather, soils, crop management, and genetic factors. We hypothesize that crop growth models can be used as strategic planning tools with historical weather to improve production or as in-season agro-advisories to advise on weather-induced production problems, and disease management. The DSSAT V4.0 crop models were simulated for soybean and maize for 28 years at Patancheru, and for groundnut for 32 years at Anantapur, to hypothesize optimum sowing date, irrigation requirement, cultivar (soybean), and N requirement (maize). Optimum sowing for these crops was generally as soon as monsoon rains allowed. Across all sowing dates, the optimum soybean cultivar was Maturity Group 8 and yield was increased 1500 kg/ha with irrigation. Maize yield increased up to 150 kg N/ha, producing 5800 kg/ha under early sowing. Irrigated maize yield was increased with later sowing dates, but irrigation requirement was high. Optimum sowing window for groundnut at Anantapur was 15 July to 15 Aug and yield was clearly water-limited. Concepts for linking dynamic disease simulation models to the CROPGRO model for predicting consequences of leafspot disease on groundnut production were discussed.

Keywords: Crop models, weather, disease, groundnut, maize, soybean

Seasonal and daily variations in weather determine cropping practices and are major determinants of yield, diseases, and quality of production throughout world, including India. The seasonal patterns in rainfall, temperature, and solar radiation influence what crops are grown and what time of year to sow. In addition, daily weather variability within these seasonal patterns includes stressfully high or low temperature, rainfall that causes flooding and anaerobic soil conditions, or lack of rainfall that causes plant water deficit. Water deficit not only reduces crop production, but drought in combination with rising air and soil temperatures enhances aflatoxin risk in groundnut (Dorner *et al.*, 1989) and cereals such as maize and sorghum. Excessive rainfall and high humidity, on the other hand, enhance foliar diseases which reduce crop yield, and in the case of groundnut, cause up to 50% reduction of yield in the absence of fungicide application (Smith and Littrell, 1980).

Crop simulation models are being more widely used over the past 20-30 years by scientists to hypothesize ways to improve agricultural production under seasonal and daily variability in weather. These models capture much of what we know about crop growth responses to factors of temperature, solar radiation, rainfall, soil traits and crop management (Boote *et al.*, 1998). Crop models have been used to evaluate management practices to improve yield for a given climatic region (Boote *et al.*, 1996; Singh *et al.*, 1994a, 1994b), to plan water withdrawals (Hook, 1994), and to evaluate climatic yield potential for different regions (Aggarwal and Kalra, 1994) or different soils (Alagarswamy *et al.*, 2000). Management practices include sowing date, row spacing, sowing density, cultivar choice (both season length and genetic traits), irrigation water availability, and N fertilizer application. Variability of rainfall (onset, intensity, ending) as well as temperature, daylength, and solar irradiance are important climatic factors that impact management practices, cultivar choice, and genetic traits to improve production in a given region. Relative humidity is an additional important determinant of foliar disease development, and the weather and soil water traits determine drought and soil temperature which enhance aflatoxin production in grains and groundnut.

The goal of this paper is to illustrate how crop

Table 1 : Correlation coefficients between weather parameters disease initiation and disease development

Weather variables	Initiation period				Disease development period			
	2002	2003	2004	2005	2002	2003	2004	2005
Degree days	0.654**	0.845**	0.952**	0.538**	0.938**	0.928**	0.866**	0.930**
Morning RH (%)	0.540*	0.875**	0.965**	0.756**	0.586*	0.502*	0.546*	0.687*
Evening RH (%)	0.102	-0.012	0.124	0.396	0.404	0.008	0.135	0.208
Rain fall (mm)	0.512*	0.568*	0.627*	0.725*	-0.587	-0.699	-0.500	-0.476
Leaf wetness hours	0.514*	0.612*	0.531*	0.601*	0.676*	0.553*	0.526*	0.634*

* Significant at 5% level, ** Significant at 1% level; During initiation period, every day weather variables of four days prior to lesion appearance and disease incidence were used for calculating correlation coefficients and after disease initiation, weather variables of every 10 days and disease incidence have been used for calculation.

growth models can be used as tools to hypothesize improvement in agricultural production (strategic planning with historical weather data), as in-season agro-advisories to warn of current-weather-induced problems in production, and as in-season agro-advisories for disease management. We also describe conceptual approaches for how disease effects on crop growth and yield can be accounted for in the CROPGRO model by two different modes: 1) via pest-coupling points and entry of scouting damage effects (as percent defoliation and percent necrosis) as illustrated by Boote *et al.* (1993) and as simulated for groundnut by Naab *et al.* (2004), or 2) by directly coupling a daily leafspot epidemic model to CROPGRO-Peanut (formerly PNUTGRO) model (Bourgeois, 1989).

MATERIALS AND METHODS

We used the DSSAT V4.0 crop growth models (Jones *et al.*, 2003, 2004) to hypothesize improvement in production of soybean and maize crops for the Hyderabad region, and production of groundnut for the Anantapur region of India, using 28 years of long-term weather data from Patancheru and 32 years for Anantapur. The Alfisol soil used at Pathancheru was widely calibrated and tested with the PNUTGRO model for accurate prediction of soil water extraction and soil surface evaporation over time in the groundnut experiments of Singh et al. (1994a, 1994b). The soil was 140 cm deep and contained 118 mm of plant extractable soil water. Soybean and maize were assumed to have the same rooting profile shape as used for groundnut, and the soil fertility factor (SLPF) was 0.92 (the same value is used in Gainesville, Florida: a value of 1.00 used for Midwestern USA soils implies no fertility limitation from P, K, pH, or micronutrients). The soil profile was set to 50% of field capacity prior to the start of simulations, with assumption that prior crops and long dry season depleted soil water to that level. To evaluate effects of sowing date over multiple years of weather, we used the automatic sowing window option in the model with the SEASONAL analysis. The automatic sowing date window was 30 days wide, and allowed sowing only if soil water was greater than 70% but less than 90% of field capacity for the top 30 cm. This forced the model to wait until sufficient rains came to bring the topsoil water content above 70%, but prevented sowing during high rainfall days and delayed sowing a short time after rains ended to allow some soil evaporation. It was important that the soil NOT be initiated at field capacity, which is the default for the soil file creation, as results were very different for the sowing date window method if the model started at field capacity (basically sowed at first opportunity). The DSSAT V4.0 software has SEASONAL software that allows analyzing the effects of management practices over multiple years of weather data, giving mean yields, probability distributions of yields, and allowing selection of treatments with high yield and low variance. Management effects on grain yield, evapotranspiration (ET), N uptake, and N leaching were determined with these analyses tools. For soybean, we tested the effects of maturity group (MG) selection, sowing date, and irrigation on production. For maize, we tested the effect of N fertilization, sowing date and

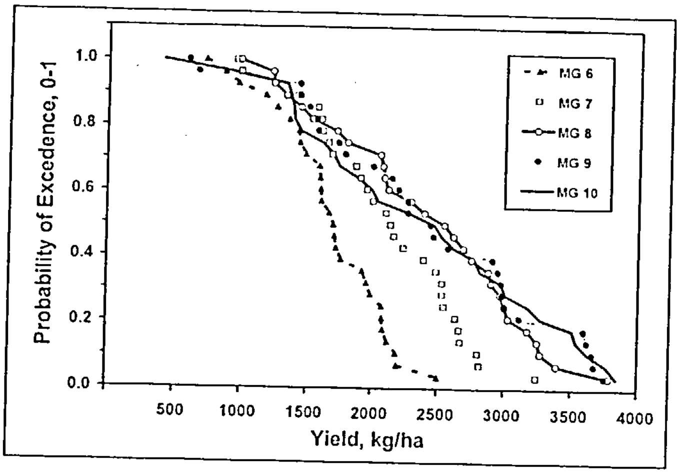

Fig. 1: Probability of attaining a given grain yield for five soybean maturity groups under rainfed conditions under early sowing window, for 28 weather years at Patancheru, India.

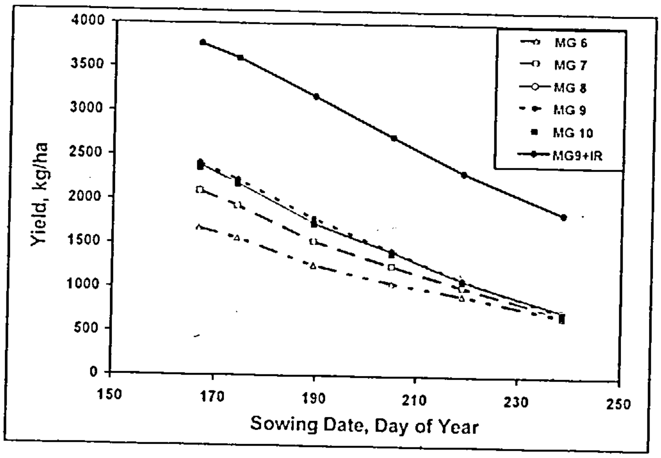

Fig. 2: Simulated soybean grain yield response to sowing date for five maturity groups under rainfed and irrigated conditions averaged over 28 weather years at Patancheru, India.

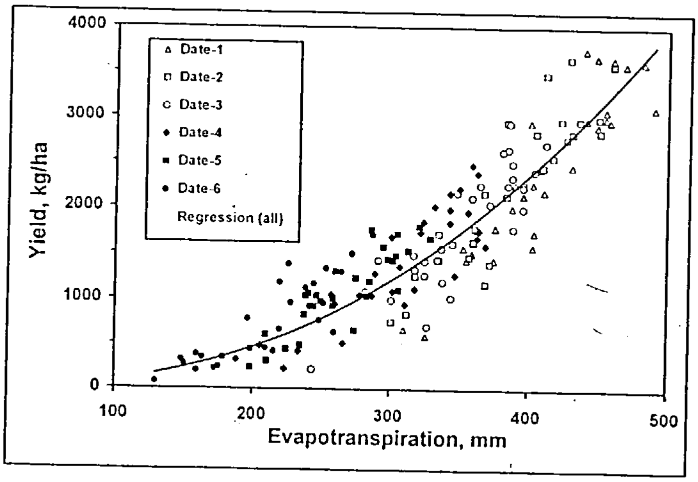

Fig. 3: Relationship of simulated soybean grain yield response to evapotranspiration for six sowing dates for MG 9, averaged over 28 weather years at Patancheru, India.

irrigation. Yield response to ET and transpiration was determined.

RESULTS AND DISCUSSION

Soybean is enjoying a surge in production in India to meet needs for protein and oil; thus, it will be interesting to know whether some of the following hypothetical evaluations relate to real practice in India. The CSM-CROPGRO-Soybean model was used to evaluate optimum MG and sowing date for the Patancheru location, under rainfed conditions for the Alfisol soil, and 25 plants/m^{-2}. We tried maturity groups from 7 to 10, based on our knowledge that MG 7 is optimum in Gainesville (29.63 degrees N), and that Patancheru is closer to the equator (17.53 degrees N) and would need later MG. Given the requirement of achieving 70% available soil water in top 30 cm, the earliest possible sowing varied from day of year 152 to 188 over the 28 seasons (June 1 to July 7, mean of day 167 or June 16). A desired sowing date window of May 15 to June 15 failed to sow in 14 out of 28 years, and the May 30 to June 30 window failed to sow in 3 out of 28 years, meaning that the monsoon came after June 30 in 3 of the years. When sown on these earliest optimum sowing dates, the simulated soybean grain yields were 1668, 2084, 2376, 2388, and 2336 kg ha^{-1} for MG 6, 7, 8, 9, and 10, respectively. The longer cycle cultivars (MG 8, 9, and 10) were the highest yielding cultivars and best able to take advantage of the full season. But a disadvantage is that seasonal ET was increased progressively for longer cycle cultivars: 319, 354, 387, 411, and 425 mm for MG 6, 7, 8, 9, and 10, respectively, thus leaving less extractable soil water at the end of the season. Fig.1 shows the probability of attaining a given yield for the MG classes over the 28 seasons. While MG 8, 9, and 10 had similar high yield potential, MG 9 and especially MG 10, had more risk of low yield in low rainfall seasons, giving them a higher yield variance but not necessarily higher yield. So MG 8 or 9 would be recommended, if sowing was on optimum first date after monsoon onset.

Soybean yield was highest for sowing in the May 30 to July 15 window (sowing on first occurrence of 70-90% available soil water), and yield progressively declined with later sowing dates (Fig. 2). This response to sowing date is like that observed in USA and certainly happens in India as well, because the short-day soybean flowers sooner and matures sooner when sown on shorter daylengths, thus causing reduced leaf area index as well as shorter cycle for grain filling. All the MG had qualitatively the same response to sowing date, but the yields at early dates were higher for MG 8, 9, and 10. The MG 8 and 9 would be the preferred cultivars regardless of sowing date, because MG 10 had higher leaf area and its lateness placed grain fill into drier weather which affected yield and left the soil water more depleted. Probability of attaining a given yield level for different sowing dates (data not shown) indicated that earlier sowing was generally better for yield. So the recommendation would be to try to sow as soon as possible after onset of reliable monsoon. Seasonal crop ET was progressively reduced with later sowing dates, because of shorter soybean life cycle and water deficit. The start of simulation was triggered at start of each sowing window to minimize soil evaporation prior to actual sowing. The seasonal ET was greater for earlier sowing. At the end of the season, there was about 45 to 65 mm of extractable soil water left in the profile compared to 118 mm at field capacity. The residual soil water was less for late sowing dates. Potential irrigation requirement was evaluated with "automatic" irrigation at a threshold of 40% of available soil water left in the top 40 cm of soil. With irrigation, for MG 9, yield was increased about 1500 kgha^{-1} compared to rainfed yield across sowing dates (Fig. 2). The average amount of irrigation required ranged from 173 to 204 mm per season applied as 5 to 6 irrigations.

The data from sowing date simulations for MG 9 were used to evaluate soybean yield response to ET and transpiration. As expected, later sowing resulted in lower ET, as the crop had a shorter life cycle. But the yield response to ET shown in Fig. 3 also includes reduced ET from rainfall deficiency. A power regression curve nicely fit the grain yield versus ET data when all six sowing dates were combined. The curvilinear nature of yield response to ET in the early to middle part of the curve is where increased rainfall frequency progressively increases soil evaporation until the canopy cover causes soil evaporation to reach a limit. The relationship of grain yield to transpiration was more linear (data not shown).

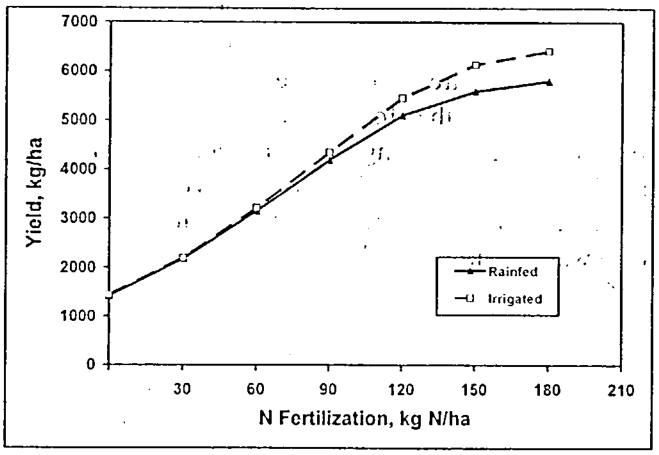

Fig. 4: Simulated maize grain yield response to N fertilization under rainfed and irrigated conditions when sown in early sowing window, over 28 weather years at Patancheru, India.

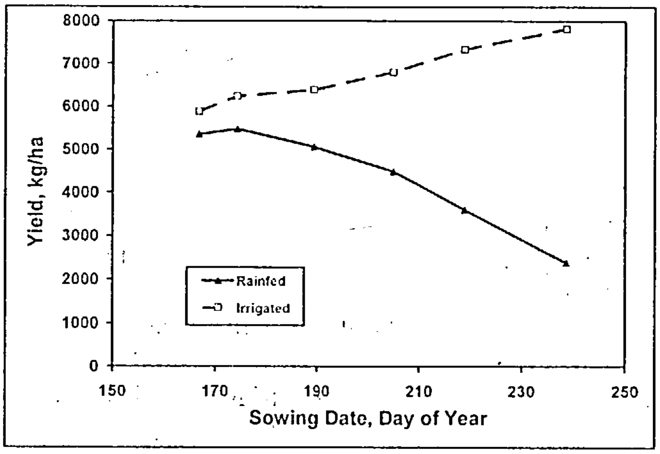

Fig. 5: Simulated maize grain yield response to sowing date under rainfed and irrigated conditions, with 120 kg N/ha, averaged over 28 weather years at Patancheru, India.

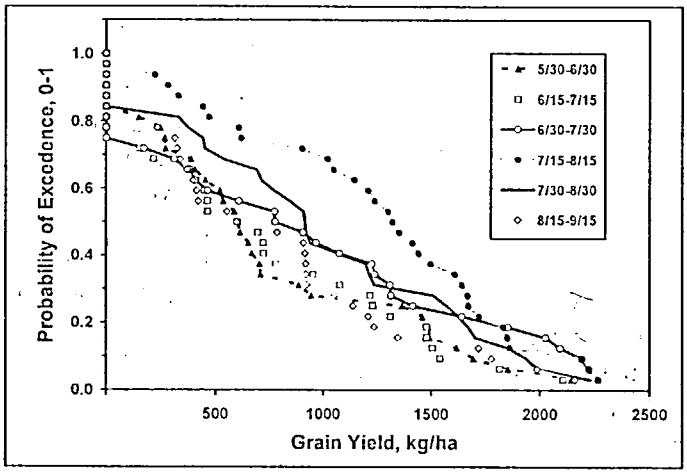

Fig. 6: Probability of attaining a given grain yield for Robut 33-1 groundnut at Anantapur, India, over 1962-1993 seasons under rainfed conditions for six sowing date windows.

The CERES-Maize model in DSSAT V4.0 was used as a tool to evaluate maize yield response to N fertilization, yield response to sowing date, and irrigation requirement using 28 years of weather for Hyderabad (Patancheru). The same soil and rooting profile was used with the same initial conditions of 50% of available soil water and 25 kg N/ha available in the profile. The sowing density was 6 plants/m^2 and the hybrid was Pioneer 304C (a longer season subtropical hybrid), although the G2 grain number was increased from 687 to 750 and G3 grain growth rate increased from 6 to 7 mg/grain/day (to increase potential yield). Fertilizer N was applied in two splits, at sowing and 45 days later.

Maize grain yield on this Alfisol soil appears to be constrained by N deficit, as N fertilization up to 150 kg N/ha increased N uptake and grain yield to about 5,800 kg/ha under rainfed conditions when sown on the earliest favorable soil moisture conditions with the monsoon (Fig. 4). Fertilization up to about 90 to 120 kg N/ha also increased the simulated ET, associated with greater LAI and water extraction. The N leaching was increased by N fertilization levels above 90 kg N/ha. Response to N fertilization was enhanced by irrigation (when soil water was depleted to 40% of available in the top 40 cm), but only when N was above 60 kg N/ha. At 180 kg N/ha rate, irrigation increased yield from 5,800 to 6,420 kgha^{-1}.

Maize yield response to sowing dates was evaluated, using 120 kg N/ha fertilization, with sowing date windows conditioned on soil water between 70 to 90% of field capacity in top 30 cm. Sowing soon after the onset of monsoon was important for rainfed maize yields (Fig. 5), primarily because the crop ran out of water during grain fill if sown too late. Good rainfed yield potential, above 4500 kgha^{-1} in 85% of years, and low variance for yield, occurred with the earliest two sowing windows. Low ET variance and ET above 380 mm per season was also achieved with the two earliest sowing windows. These early sowing dates had more extractable soil water left at maturity, compared to the later dates which left less than 40 mm of extractable soil water in 80% of the cases. Irrigation gave greater increase in maize yield for the later sowing dates than the early sowing dates (Fig. 5), confirming that late sowing exposed maize to water deficit. Interestingly, under irrigation, the later-sown maize crop produced higher yields than the early-sown crops, possibly because the cooler weather in fall was favorable to allow a long grain filling period. However, irrigation requirement for maize increased progressively with later sowing, doubling from 148 to 425 mm from the first sowing to the latest sowing date.

Groundnut yield was simulated for the Anantapur region for several reasons. First, this region is a dominant groundnut-growing region for India despite deficit rainfall, thus allowing us to evaluate the groundnut model sensitivity to rainfall and yield response to ET. Second, the lack of rainfall and low humidity reduce leafspot disease problems thus allowing us to more accurately use the groundnut model despite its current lack of accounting for disease effects on groundnut production. Indian researchers successfully used an earlier version of the model (PNUTGRO) to predict yield response to rainfall in the Anantapur region (Singh *et al.*, 1994a, 1994b). For this region, we used a soil profile from Singh *et al.* (1994a) that was 120 cm deep, with 98 mm extractable soil water and SLPF of 0.77. The crop was grown under rainfed conditions at 28 plants/m^2 in 30-cm row spacing, using weather data from 1962 to 1993. Sowing windows of 30 days were evaluated, with sowing triggered when soil water was between 70 to 90% of field capacity.

The sowing window of July 15 to August 15 was most reliable, giving the highest probability of attaining high yield (Fig. 6). The 30-day windows starting May 30, June 15, June 30, July 15, July 30, and August 15, gave mean grain yields of 873, 946, 1201, 1280, 1140, and 918 kgha^{-1}, respectively. This mean yield does not include the failed sowings which numbered 6, 9, 9, 2, 6, and 7 years out of 32 years per sowing window. Groundnut yield versus ET or transpiration had similar relationships as soybean, and confirmed that low yields were caused by rainfall deficit.

Disease effects on groundnut growth and yield can be accounted for in the CSM-CROPGRO-Peanut model (Boote *et al.*, 1998; Jones *et al.*, 2003), by two different modes: 1) via pest-coupling points and entry of scouting damage effects (as percent defoliation and percent necrosis) as illustrated by Boote *et al.* (1993) and as

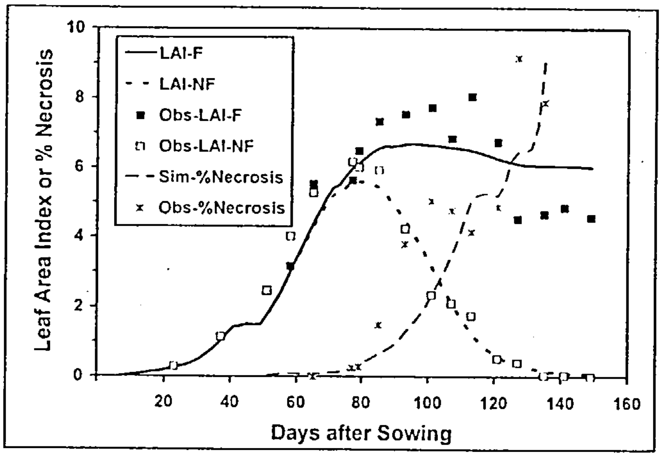

Fig. 7: Simulated leaf area index for fungicide-treated and non-treated crop, and simulated percent necrosis for untreated Florunner peanut grown in 1986 at Gainesville, FL.

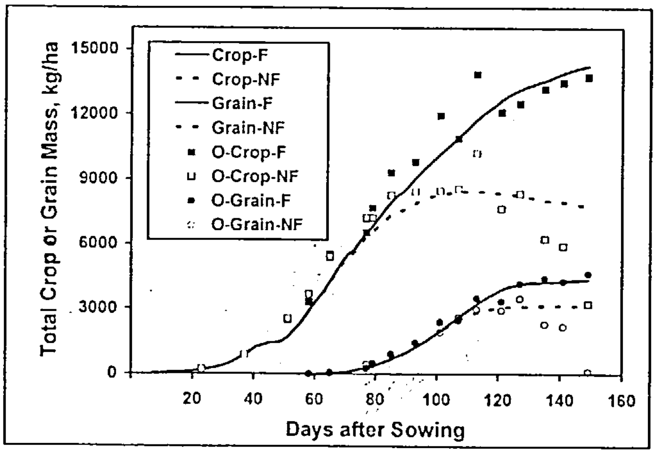

Fig. 8: Simulated crop and grain mass for fungicide-treated and untreated Florunner peanut grown in 1986 at Gainesville, FL with leafspot and defoliation predicted by LATESPOT model of Bourgeois (1989).

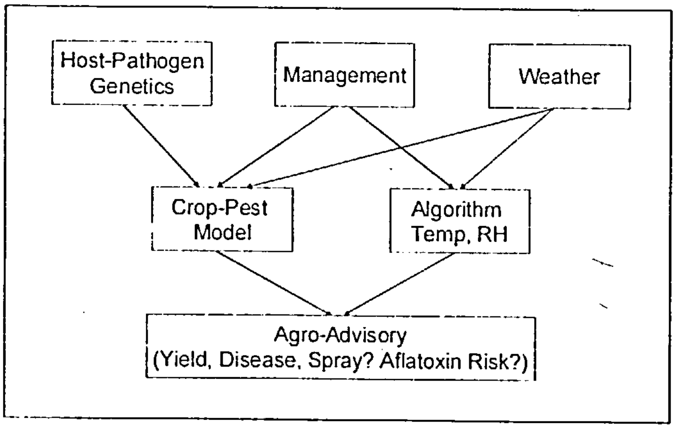

Fig. 9: Conceptual scheme for agro-advisories with crop-pest models and algorithms using weather, management, and crop-pathogen information.

simulated for groundnut by Naab *et al.* (2004), or 2) by directly coupling a daily leafspot epidemic model to the crop growth model (Bourgeois, 1989). Conceptual and operational approaches to predict yield response to pest damage with crop growth models were described by Boote *et al.* (1993). The CSM-CROPGRO-Peanut model was derived from the PNUTGRO model (Boote *et al.*, 1991) and was shown to successfully predict groundnut growth responses to soil water deficit, sowing date, sowing density, and other management factors in India (Singh *et al.*, 1994a,b).

In 1989, Bourgeois developed a mechanistic leafspot model (LATESPOT) coupled to the PNUTGRO model. We have linked LATESPOT to more recent version of the CROPGRO-Peanut model. Each day's new leaf area production is placed into age classes (cohorts) that age daily and become infected with *Cercospora* depending on daily weather. The leafspot infections on those leaves progress through their latent phase, then lesion area begins to expand, and finally sporulation occurs from the lesion area when weather is favorable. The released spores then infect other leaves in the crop, thus creating a polycyclic epidemic. After a period of spore release, lesions become non-sporulating and modeled leaf abscission is conditioned by leaf age, canopy-shading, and extent of leafspot. Leaf infection by spores is a probabilistic function of spore numbers and is enhanced by favorable temperatures and humidity. The latent period, lesion expansion rate, and sporulation rate vary with temperature in a function that depends on both the *Cercospora* spp, and the groundnut cultivar. Cultivar resistance is expressed as longer latent period, slower lesion expansion rate, and lower sporulation rate. Timing of leaflet abscission versus leafspot necrosis is a cultivar-dependent trait. Loss of leaf area over time and increased presence of necrotic area for the unsprayed crop (Fig. 7) reduce simulated canopy photosynthesis and production. Fig. 8, simulated with the LATESPOT model of Bourgeois (1989), illustrates simulated disease effects on total crop mass and grain mass for fungicide-treated and untreated Florunner peanut under high leafspot pressure in Florida.

The CROPGRO-Peanut model was modified by Boote and Prasad (unpublished, 2003) to predict *Aspergillis niger* infection and aflatoxin production in groundnut pods as affected by plant water deficit, pod zone water content, and pod zone soil temperature. The crop model produces successive daily individual cohorts of pods, with associated pod age, seed growth, daily plant water status, pod zone soil water content, temperature of the podding zone. These conditions are used to regulate infection by *Aspergillis* fungus, and to regulate synthesis of aflatoxin in infected pods. The model keeps track of number (and percentage) of pods/seeds infected, amount of aflatoxin (mass and concentration) for seeds in all age classes of pods. The percent infection, aflatoxin concentration (average over all seeds), and distribution of aflatoxin concentrations in categories of seeds, is available for output on any given date. The preliminary model was tested against data from the ICRISAT-Sahelian Center, Niger (Craufurd et al., 2006), and shown to give reasonable differences between irrigation and sowing date treatments.

The use of crop growth models and coupled crop-pest simulations is very helpful to improve our understanding and integration of weather, soils, and management factors affecting production and diseases of crops. Nevertheless, it is important to consider the value of simple agro-advisory algorithms to predict the timing to apply fungicides to control leafspot diseases or to warn of a possible aflatoxin problem. Leafspot-spray advisories have been developed for groundnut and used in the USA to indicate the best timing of leafspot spray applications. We propose that crop models or weather algorithms can be used as agro-advisory aids (Fig. 9) to give fore-warning of probable weather effects on crop yields, leafspot disease, or fungicide-spray requirements (infectivity phase) or aflatoxin contamination of grain/seed. Based on these advisories, farmers can react appropriately and governments can make alternate plans. Based on the advisory information, producers can spray fungicide in next few days, irrigate soon to improve yield or quality (reduce aflatoxin), or farmers and government can anticipate when yields will be less than expected or disease risk higher. We conclude that crop simulation models and weather service delivery technologies are ready for more advanced use as agro-advisories, both as strategic pre-season tools and as in-season advisories.

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