Modelling impact of climate variability on rainfed groundnut

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We present here a heuristic model for the indirect impact of climate variability via the triggering of pests/diseases/weeds for rainfed groundnut over the Anantapur region. A simple hydrological model is used to determine the soil moisture for the rainfall pattern, in any given year. The criteria for determining when specific farming operations, such as ploughing and sowing, are performed are defined in terms of the soil moisture, on the basis of the farming practices in the region. With the sowing date so determined, the dates of occurrence of the different life history stages are known for any specific year. The events that trigger the growth and incidence/infestation of the major pests/diseases, viz. wet/dry spells, are also defined in terms of the soil moisture and/or rainfall. The probabilities of the occurrence of the different pests/diseases incorporated in the model are then calculated by running the model for eighty years for which daily rainfall data at the Ananthapur observatory have been obtained from the India Meteorological Department. The model has been validated by comparison of the results with the observations of the incidence/infestation of specific pests/diseases at the Anantapur agricultural station of the Andhra Pradesh University.

The PNUTGRO model, which is a complex model for the growth and development of the groundnut plant, is able to simulate well the variability of the yield at the Anantapur agricultural station, where pests and diseases are prevented by plant protection measures. However, the observed district yields are generally much lower. We find that when the heuristic model for pests/diseases is used in conjunction with the PNUTGRO model, the simulated variation of the yield during 1970–90 is rather close to the observed district yield. This suggests that such models which incorporate the direct impact of climate on growth and development as well as the indirect impact via triggering of pests and diseases can be used for understanding the response of the groundnut yield to climate variability and in decision support systems for the region.

IT is well known that the agricultural production of rainfed regions (which constitute about 65% of the area under cultivation and account for about 50% of the total production in our country[1], varies a great deal from year to year, in response to the variability of the climate and particularly the rainfall. The production of these regions has not increased substantially over the last three decades in marked contrast to the irrigated belt which experienced the green revolution[2].

One of the major challenges is therefore, to enhance the production of the rainfed regions in the face of the variability of the monsoon. It will be necessary to use the knowledge of climate variability (and predictions of the critical events in specific seasons, if available) to tailor the cropping patterns and the management practices over each agroclimatic zone to achieve this goal. An important tool in this endeavour is a model, which can simulate reasonably realistically the impact of climate variability over the region of interest, on the specific crop under consideration. With such models it is possible to simulate the production associated with different management options and hence identify the opti-

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mal strategies. Such models are also necessary for realistic assessments of the impact of climate change such as that expected from the increase in concentration of the greenhouse gases.

Climate variability has a direct impact on the growth and development of crops as well as an indirect impact via triggering of pests/diseases/weeds. Crop models developed over the last few decades for the different crops such as rice, wheat, groundnut, sorghum, etc. incorporate only some facets of the direct impact of climate variability[3,4]. Thus while all the models incorporate the impact of radiation on photosynthesis, and hence growth and development of the plant, only a few models (e.g. PNUTGRO for groundnut[5]) incorporate the effects of moisture stress induced by dry spells. This is because most of the models were developed for irrigated conditions for use in understanding the production associated with different varieties, different levels of fertilizer inputs, etc. None of the crop models incorporate the indirect impact of climate variability via triggering of pests/diseases/weeds.

We have developed a heuristic model for this indirect impact of climate via these yield-reducing factors. The aim is to develop the methodology for assessing this component of the total impact of climate variability on

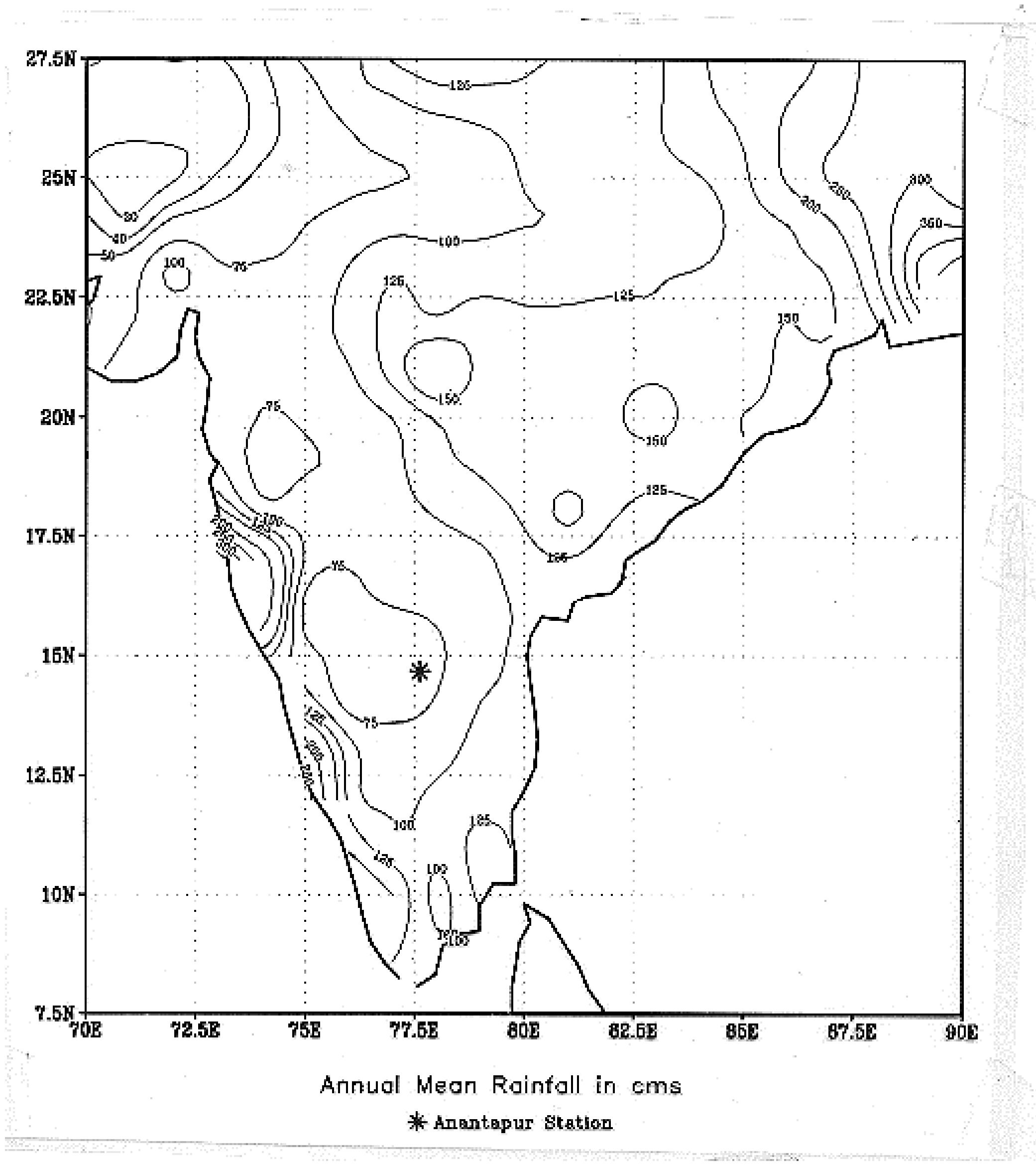


Figure 1. Variation of annual rainfall over the peninsula, the location of Anantapur is indicated.

agricultural productivity. However the model is developed for a specific crop (rainfed groundnut) for a specific region (the Anantapur region), which is a semi-arid part of the peninsula (Figure 1). Rainfall data for eighty years have been obtained from the India Meteorological Department for Anantapur observatory. The average annual rainfall is only 57 cm; there are large variations in the rainfall from year to year resulting in a standard deviation of 16 cm. The rainfall variations within a year are also large with intermittent wet spells and dry spells (Figure 2), which are reflected in the large variation of the weekly rainfall (Figure 3). The year-to-year variation in groundnut yield is also very large because most of it is grown in rainfed conditions. The yield varies from less than 500 kg/hectare (which is considered as failure of the crop) to a little over one ton per hectare. Singh *et al.*[6] have shown that the variation in yield at the Anantapur agricultural station (at which the infestation/infection of most of the pests/diseases is prevented by plant protection measures) is well simulated by the PNUTGRO model (Figure 4). Note that in some years the PNUTGRO yield is less than the observed yield. We shall see in later sections that such years are characterized by deficit rainfall. This suggests that PNUTGRO underestimates the tolerance to moisture stress.

Generally, the district yield is much less than the PNUTGRO yield (Figure 5). The farmers in this region do not apply pesticides since the yield is not high and varies a great deal from year to year and quantitative assessments of the expected benefits of application of pesticides in terms of yield enhancement are not available. We therefore expect that a large part of the gap between the PNUTGRO yield (which we may take as the potential yield in the rainfed situation) arises from losses due to incidence/infestation of pests/ diseases.

We present here a heuristic model for the indirect impact of climate, viz. triggering of pests and diseases.

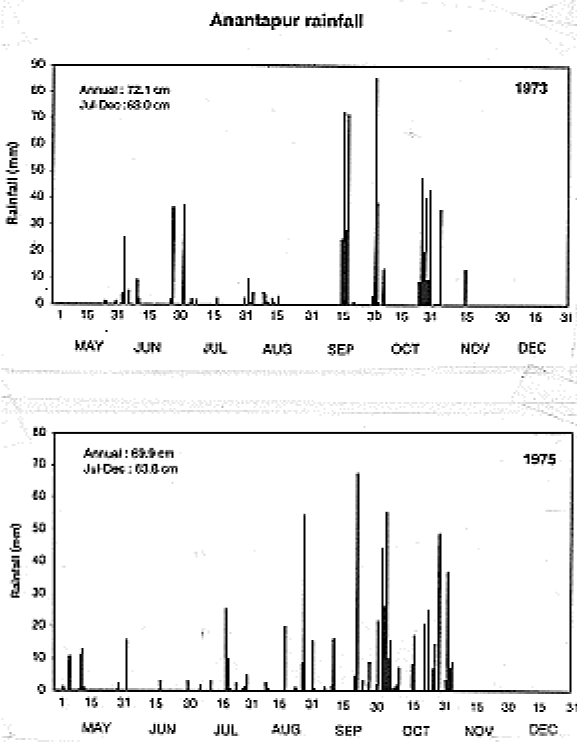
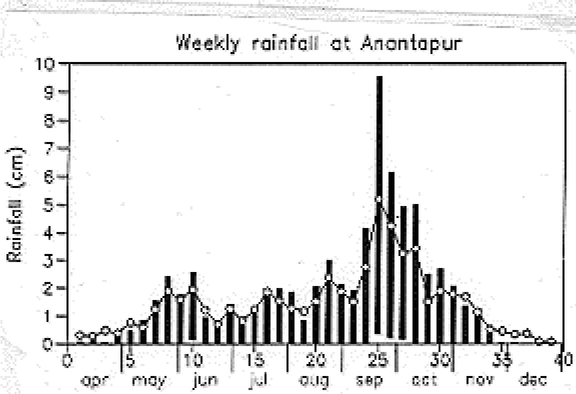


Figure 2. Variation of daily rainfall during May to December of 1973 and 1975 at Anantapur.



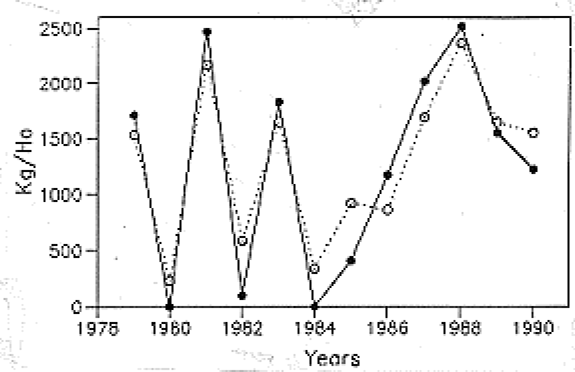


Figure 4. Variation of the observed yield at the Anantapur agricultural station and yield simulated by PNUTGRO model during 1979 to 1990 (after Singh *et al.*[6]). Solid circles PNUTGRO.

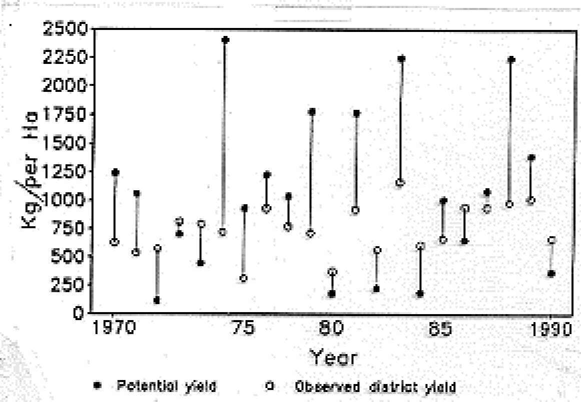


Figure 5. Variation of the observed district yield and the yield simulated by the PNUTGRO model.

Figure 2. Variation of daily rainfall during May to December of 1973 and 1975 at Anantapur.

Figure 3. The circle represents the mean weekly rainfall and the bar covers 50% of years (75% of years below top edge and 25% below bottom edge): data period 1911 to 1990 (source: IMD).

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Since the timing of the farming operations as well as triggering of some of the pests/diseases depend on the soil moisture, first a simple hydrological model for derivation of soil moisture is considered. Then a heuristic model in which the timing of the farming operations in any year as well as the triggering of different pests/diseases/weeds are determined on the basis of criteria defined in terms of the soil moisture and/or rainfall, is described. The results of the heuristic model using the available rainfall data at the Anantapur meteorological observatory (1911–1990) to derive probabilities of the incidence/infestation of pests/diseases are discussed. A comparison of the results of the heuristic model for the rainfall data of the agricultural station at Anantapur for 1970–90 with observations of the sowing dates and incidence of two major pests/diseases is also presented. Finally, we discuss the results of using the heuristic model in conjunction with the PNUTGRO model to derive the integrated impact of climate variability for Anantapur for the period 1970–90 and show that the yield thus simulated is rather close to the observed district yield. Analysis of the variation of the potential and district yields with rainfall presented here suggests that there is considerable scope for enhancement of yield in the years with good rainfall. The last section comprises concluding remarks.

Hydrological model

We consider a simple water balance model which simulates the soil moisture from a minimal set of meteorological and other data. The variation in the moisture in the soil up to the root zone, during the growing season is one of the most important variables in determining the growth and yield of rainfed crops. The timing of the different farming operations such as land preparation and sowing, also depends upon the soil moisture. Extreme dry or wet conditions of the soil promote the growth of soil pathogens which can have a considerable impact on the yield. Thus information on the variation of the soil moisture is important for deducing the impact of climate on growth, development of the crop as well as on yield reducing factors such as pests/diseases/weeds.

Many models have been developed for simulating soil moisture[7]. An important part of the models is the estimation of the evapotranspiration, which is a complex function of many variables, such as radiation, temperature, relative humidity, wind, etc.[8–10]. Our aim is to consider the simplest model which can simulate the soil moisture (particularly the wet and dry events) at Anantapur reasonably well, which needs only the minimum data set (such as rainfall) on the daily scale for the specific year. With such a model, soil moisture variations over a large number of years can be derived using the rich meteorological data set and probabilities of critical events, which can occur during different life history stages of groundnut, worked out.

Description of the soil moisture model

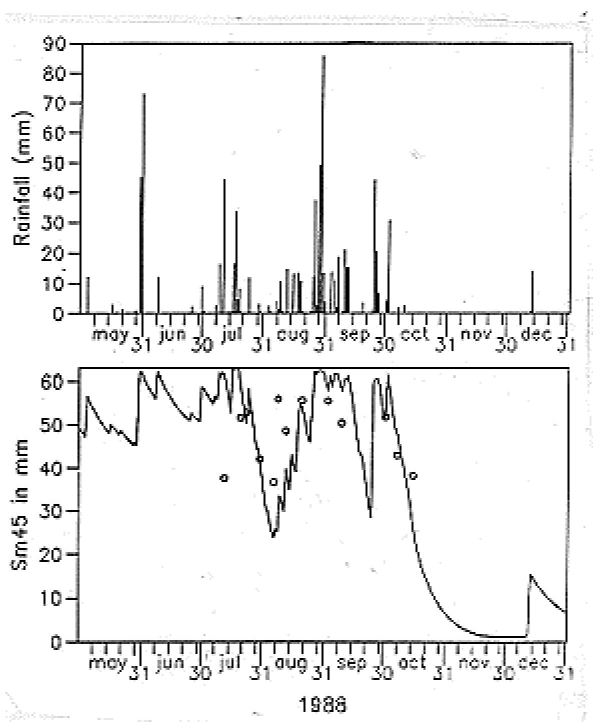
We consider a simple two-layer model in which the evaporation/evapotranspiration occurs only from the top layer, but the moisture is retained in both the layers. Runoff is assumed to occur if there is excess rainfall above the saturation level of both the layers. When the land is bare, the depth of the top layer is taken to be 15 cm, since radiation cannot penetrate beyond that. The depth of the top layer is taken to increase from 15 cm at the time of sowing to 60 cm at the time of flowering (i.e. 35 days after sowing), since the groundnut crop is expected to have developed its maximum effective root depth of 60 cm by this stage. The second layer is assumed to extend from the bottom of the top layer up to 60 cm. Thus the depth of the second layer is taken to be 45 cm before planting and decreases with time until after 35 days after sowing, there is only one layer of 60 cm in depth.

The daily soil moisture is computed by a one-dimensional water balance approach[11]. Since we are interested in rainfed conditions, it is assumed that the rainfall is the only source and the soil moisture is depleted by evaporation or evapotranspiration (depending on whether it is bare soil or cropped land). Runoff is assumed to occur if there is excess rainfall above that required for saturation of both the layers. Evaporation from bare soil is assumed to occur at a rate proportional to the moisture content of the soil. Evapotranspiration estimation from cropped land is the major component of soil moisture modelling. Daily evapotranspiration (ET) is modelled as proposed by Rijtema and Aboukhaled[12]. ET is calculated from the potential crop evapotranspiration (ET_{crop}) which is obtained from daily pan evaporation measurements using the pan coefficient (K_p) and crop coefficient (K_c) following the procedures recommended by Doorenbos and Pruitt[13]. The model is briefly described here. The details are given in Sridhar[14].

The roots of the plant cannot suck water from the soil, if the soil moisture is below a certain value and the plants begin to wilt permanently. This value of soil moisture, below which there is permanent wilting, is termed as the permanent wilting point (PWP). The maximum moisture that the soil can hold is termed as field capacity (FC). If FC and PWP are expressed as mm of moisture per unit depth of the soil, then the maximum soil moisture available to the plant, denoted by S_a is given by the product of (FC–PWP) and the root depth. Field capacity and permanent wilting point depend upon the characteristics of the soil. For the sandy loamy soil of Anantapur fields, we take the field capacity to be 24% and permanent wilting point to be 10%. This implies that the maximum available moisture S_a is 14%.

The ET of the plants is equal to the potential crop evapotranspiration (ET_{crop}) when there is sufficient amount of moisture in the root zone. However, if the moisture in the root zone gets depleted far below the level of S_a, ET is reduced. Most of the plants can tolerate certain amount of depletion (S_a*P, $P < 1$, where P is called as tolerable depletion fraction) of soil moisture from the maximum S_a and can still maintain transpiration at the potential level. Thus ET will still be the potential evapotranspiration (ET_{crop}) demanded by the atmosphere as long as the moisture in the root zone
is above ($S_a – S_a*P$). Given the daily rainfall and pan evaporation, the daily soil moisture is simulated by the model.

The simulation assumes bare land till a day before sowing and cropped land from the date of sowing to the harvest date. Figure 6 shows the simulation of the variation in soil moisture for 1988 along with the observations at the Anantapur agricultural station and the variation in rainfall. It is seen that the wet and dry spells are reasonably well captured.



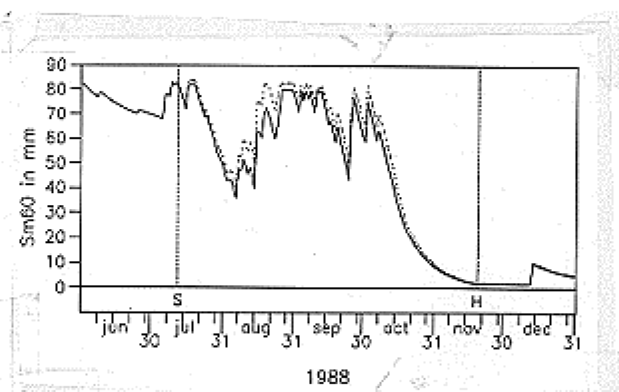


Figure 7. Variation of soil moisture using daily pan evaporation data (solid line) and pan evaporation interpolated from monthly mean pan evaporation (dashed line).

Figure 6. Variation of rainfall at Anantapur (above) and the simulated soil moisture and the observed soil moisture (circles) for 1988 (below).

Figure 7. Variation of soil moisture using daily pan evaporation data (solid line) and pan evaporation interpolated from monthly mean pan evaporation (dashed line).

Since daily data of pan evaporation (PE) not available for many stations and for many years, we tested the sensitivity to daily observed PE comparing with the results based on the daily values for PE obtained by a polynomial fit to the mean monthly climatological PE values. The daily soil moisture simulated by the model using the observed daily values of PE is found to be rather close to that using the daily PE values from monthly climatological values (Figure 7). This is because the soil moisture is predominantly determined by daily rainfall and day-to-day variations of PE have little impact.

Thus we now have a simple hydrological water balance model to simulate daily soil moisture with minimum meteorological data (daily rainfall), which can capture fluctuations in soil moisture between wet/dry spells.

The model needs further validation for different types of years and can be modified if necessary. The model can be very easily adopted for other regions with different climatic conditions and different types of soil characteristics. Since the model requires daily values of only rainfall data, this simple model can be used to simulate time series of soil moisture over the large network of meteorological stations at which daily rainfall data are available.

Heuristic model for the indirect impact of climate

We describe here a heuristic model for assessing the indirect impact of climate via triggering of pests/diseases/weeds, developed for a specific region (Anantapur) and for a specific crop (groundnut). The losses that arise from the yield-reducing factors considered in this model can be estimated for each year for which the rainfall data are available. We use this model in conjunction with the PNUTGRO model which simulates the potential yield for the specific year to derive the expected yield in the presence of pests, diseases and weeds.

It is known that the productivity of rainfed crops depends not only on the seasonal/monthly total values of the important meteorological variables, but also on the distribution within the season[15–17]. In particular, the occurrence of some climate events such as wet/dry spells has a large impact on the productivity of the crop. Dry spells induce moisture stress and have a major impact on growth and development when they occur at some life history stages. Such impacts are incorporated in the PNUTGRO model. Dry spells and wet spells can also trigger the growth of pests/diseases/weeds and hence have impact on the yield. The impact may also be on the operational efficiency, as in the case of an intense dry spell during harvest which results in difficulty in retrieving all the pods from the hard soil. These indirect impacts are incorporated in the heuristic model.

An important task in the development of the model is to identify critical climate events at different growth stages of any crop. Such an identification is a prerequisite for elucidation of the kind of meteorological information/prediction which is required for choosing between the different management options available to the farmer. This model is based on the farmers' input on (i) the critical meteorological events for triggering the major pests/diseases and weeds and (ii) the impact of each of these events. The conditions which determine the timing of the different farming operations are also based on what is practised by groundnut farmers in the Anantapur region.

Brief description of the model

The model developed is applicable specifically to the variety TMV-2 of groundnut which has been cultivated in the Anantapur region for over twenty years. In the model, firstly on the basis of the available rainfall data (1911–90) for Anantapur, the daily soil moisture is simulated by the hydrological model, which uses the minimum data set, i.e. daily rainfall and monthly average PE. The conditions for the different farming operations such as ploughing, sowing, etc. are defined in terms of the soil moisture and/or the rainfall over the region. Thus whether the opportunity for ploughing, harrowing and sowing would occur in a given year and the dates for these operations are determined for each year.

Given the sowing date, the timing of the different life history stages is known for the specific year. Hence whether critical events such as wet or dry spells occur at any specific stage (such as flowering or seedling) can be determined, provided what constitutes a critical wet/dry spell for impact on growth/development at that stage or triggering of specific pests/diseases, is clearly defined in terms of the rainfall and/or the soil moisture. A major component of this model is such a definition of the critical adverse events and a quantitative estimate of the impact in terms of percentage loss in productivity. The model is run for all years for which rainfall data are available. From this data set, the probabilities of the adverse weather events (wet/dry spells) leading to each of the pests/diseases/weeds considered in the model are calculated. From the loss simulated by the heuristic model for each adverse event which occurred in that year, the expected total loss for the year is estimated. The details of the model are discussed in the remaining sections.

Land preparation for sowing

The land preparation involving (i) first ploughing, (ii) second ploughing (when possible) and (iii) harrowing is an essential prerequisite for sowing of the crop. The conditions for the different land preparation operations and sowing are defined in terms of the soil moisture. Before sowing the crop, when the soil is bare, the evaporation is assumed to take place from the top 15 cm, hence the top layer in the hydrological model for the bare land is taken to be 15 cm. Water from rain is assumed to be retained up to a depth of 60 cm. For bare land the two layers in the hydrological model are a top layer of 15 cm in depth and the lower layer of 45 cm in depth. The depth to which the land is ploughed in this region is 20 cm. Hence the soil moisture of a layer of depth of 20 cm is calculated (by appropriate averaging of the two layers) for determining the conditions for land preparation. This soil moisture is denoted by S_m20, and the maximum available soil moisture up to a depth of 20 cm by S_a20. The conditions for the different land preparation operations and the cultural practices followed in this region by the farmers are given in Table 1.

Note that if the soil moisture up to 20 cm depth is not saturated till 25 June, the farmers go for crisis ploughing between 26 June and 30 July as soon as the land is moderately wet. If until 30 July, ploughing is not possible, groundnut cultivation is abandoned. Also, if harrowing is not possible due to continued wet conditions of the soil till 16 August, the cultivation is abandoned.

Table 1. Land preparation operations

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Operation	Date	Condition
First plough	1 May to 25 June	$S_m20 \geq 0.9 S_a20$
If the above condition for ploughing is not satisfied before 25 June, crisis ploughing is done.		
Crisis plough	26 June to 30 July	$S_m20 \geq 0.75\ S_a20$
If the above condition for crisis ploughing is also not satisfied, cultivation for that year is abandoned.		
Second plough	7 days after 1st plough or 7 June (whichever is later) to 25 June	$S_m20 \geq 0.75\ S_a20$
If the above condition for second ploughing is not satisfied, the first plough is taken as the final plough		
Harrowing	Final plough date or 15 June (whichever is later) to 16 August	$S_m20 < 0.75\ S_a20$ for 2 consecutive days.
If land is not sufficiently dry to harrow, cultivation for that year is abandoned		
Sowing	Harrowing day or 25 June (whichever is later) to 25 July	$S_m20 \geq 0.6\ S_a20$
If land is not sufficiently wet to sow till 25 July late/crisis sowing is undertaken		
Late/crisis sowing	Harrowing day or 26 July (whichever is later) to 16 August	$S_m20 \geq 0.3\ S_a20$
Day of sowing should be a non-rainy day (rainfall ≤ 0.25 mm)		

Soil depth considered = 20 cm, S_a20 = 28 mm and S_m20 = available soil moisture.

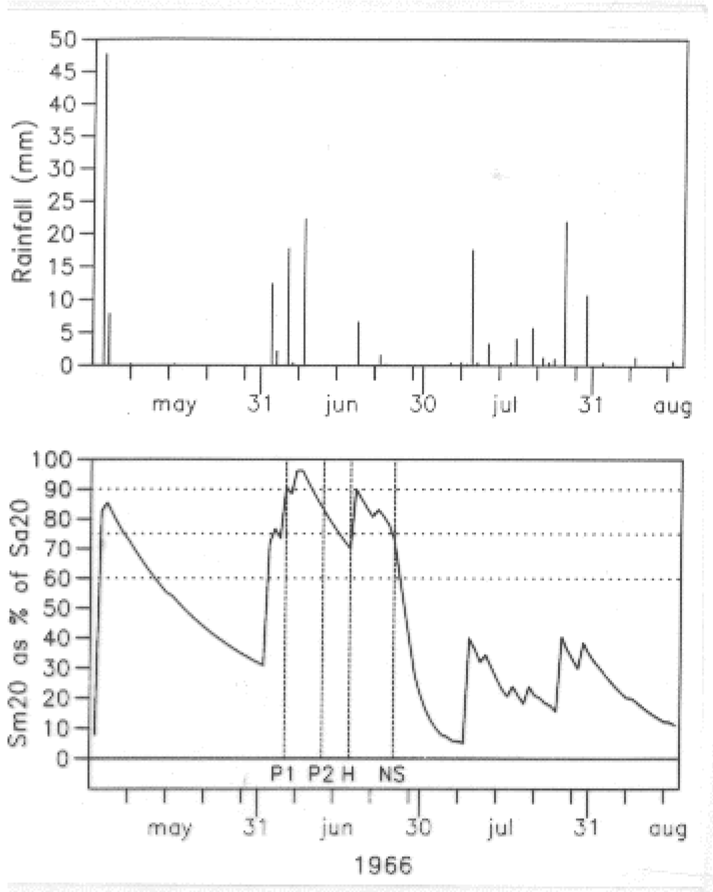

Figure 8. Variation of rainfall and simulated soil moisture for 1966 with dates of first, second plough and, harrowing and sowing indicated.

After harrowing, when the ground is sufficiently wet, the seeds are sown. Since sowing is done manually, the day of sowing has to be a non-rainy day. The variation of rainfall and soil moisture during a typical year in which all the land preparations and sowing operation are possible is shown in Figure 8. If the condition for sowing (Table 1) is not satisfied in a particular year till 25 July, farmers undertake what is called crisis sowing, when the soil is moderately wet. The first opportunity to sow after 26 July can occur with adequate soil moisture (late sowing) or when the soil is only moderately wet (crisis sowing). If, even the condition for crisis sowing is not satisfied till 16 August, groundnut cultivation for that year is abandoned. The conditions of Table 1 are applied, to see whether opportunity to plough, harrow and sow exist, and if so, the ploughing, harrowing and sowing dates are determined for each year.

It should be pointed out that in this model we have assumed sowing at the first opportunity. If for some reason, this opportunity is not utilized in some years, other opportunities for sowing do occur at a later date. The problems of determining which is the optimal date from sowing amongst the possible ones in an year and the probability of subsequent sowing opportunities given the rainfall until the first one, are extremely important for a useful decision support system. We are at present investigating these problems and the results will be reported in a subsequent paper. In this paper, we assume that sowing is done at the first opportunity.

Critical events during different life history stages of the crop

We will combine the results of this model for the losses in yield due to the different critical climatic events with the results of the PNUTGRO model for the potential yield. Hence we focus on those events which trigger the major pests/diseases or lead to the growth of weeds since these factors are not incorporated in the PNUTGRO model. In addition, we incorporate the effect of adverse climate events on some physiological events such as multiple batches of flowering, because some facets such as compensation between successive batches of flowers are not incorporated in the PNUTGRO model.

Critical events are defined in terms of the soil moisture and/or rainfall. The soil moisture of the layer up to the root depth is denoted by S_m and the maximum available soil moisture of this layer by S_a. The depth of the layer from which evapotranspiration occurs in the hydrological model is taken to increase linearly from 15 cm at sowing to 60 cm after flowering. The losses associated with adverse events at each stage are estimated. Events with a direct impact on productivity such as flowering losses, and pod losses during harvest during different life stages of crop are considered. The events which have an indirect impact on productivity by triggering pests and diseases (such as seedrot, podrot, leaf miner and late leaf-spot) and through weed growth during periods cutting across different growth stages of the crop are also incorporated. These adverse events and the associated loss with each (expressed as a percentage of the yield) are indicated in Table 2. The total loss due to climate-induced factors considered in this model in a particular year is estimated from the loss due to each adverse event that occurred. Thus, for any year, at the time of sowing we take the expected yield to be 100% (which actually corresponds to the potential yield predicted by the PNUTGRO for that year); estimate the impact of each adverse event at the stage it occurred and integrate through the year to finally arrive at the total loss in that year due to the factors considered in the model.

Flowering batches and compensation. Groundnut is characterized by an indeterminate growth habit and, flowers continuously from about 30 days after sowing up to the time of harvest. Only the flowers produced up to 75 days after sowing, can mature into pods at the time

Table 2. Adverse events at each life-history stage, the nature of impact, and the associated losses incorporated in the heuristic model

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Phenology	Days after sowing	Adverse events triggering	Impact	Loss
Germination	0 to 9	$S_m > 0.9\ S_a$ for 2 days	Seed rot	5–10%
5% loss for 2 wet days, 10% for 3 or more wet days				
1-Flower initiation	25–35	$S_m > 0.9\ S_a$ for 1 day	Flower loss	6–21%
2-Flower initiation	50–60			
1-Batch	Good		Bad	
1-Flower fraction	$p = 0.7$		$p = 0.4$	
2-Batch	Good Bad		Good Bad	
2-Flower fraction				
	0.3 0.24		0.45 0.39	
Total flowers (%)	100% 94%		85% 79%	
1-Pod formation	50–60	$S_m > 0.9\ S_a$ for 3 consecutive days	Pod rot	30% of 1-flower fraction
1-Pod filling	60–80	$S_m > 0.9\ S_a$ for 5 consecutive days	Pod rot	20% of 1-flower fraction
2-Pod formation	75–85	$S_m > 0.9\ S_a$ for 3 consecutive days	Pod rot	30% of 1-flower fraction
2-pod filling	85–105	$S_m > 0.9\ S_a$ for 5 consecutive days	Pod rot	20% of 2-flower fraction
Harvest	100–110* or 110–120	$S_m < 0.4\ S_a$ for 3 consecutive days	Difficulty in harvest	5%
Harvest	100–110* or 110 to 120	$S_m \geq 0.9\ S_a$ for 3 consecutive days	Seeds germinate	5%
*In case of loss of foliage due to leaf miner or tikka				
Leaf miner	35–110	$S_m < 0.5\ S_a$ and non rainy for 21 days	Leaf miner	10–40%
If within the first 14 leaf miner days, there is a drenching shower (rain ≥ 2 cm/day), loss is 0. Days and losses: 25 days 10%, 45 days – 15%, 60 days – 25%, ≥ 75 days – 40%, interpolate in between.				
Weed growth	35–80	$S_m \geq 0.8\ S_a$ for 7 consecutive days or $S_m \geq 0.8\ S_a$ for 14 days	Weed growth	10%
Late leafspot (tikka)	75–110	$S_m \geq 0.9\ S_a$ for 3 consecutive days or $S_m \geq 0.9\ S_a$ for 10 days	Tikka/ collar rot/root rot	5–25%
For each consecutive 3 days set 5% up to a maximum of 20% + 5% for additional other 10 or more wet days				

S_m = Soil moisture, S_a = (FC – PWP)*Depth = 8.4 cm and Depth = 60 cm.

of harvest. Such flowers (i.e those produced between 30 and 75 days after sowing) generally occur in two well-defined flushes which are called batches of flower initiation. After the first flush of flowering lasting about ten days, there is a gap of approximately 25 days and then another set of flowers is produced. Since there is a time gap between two successive batches of flowering, flower initiation, pod formation and pod filling stages corresponding to each batch of flowering are subjected to different kinds of weather events. We consider two batches of flower initiation in this model.

High soil moisture conditions during the first batch of flower initiation reduces the number of flowers by enhancing vegetative growth. After fertilization, the pegs emerging from the base of the flowers penetrate the ground and pod growth occurs within the soil. During the second batch of flower initiation, if there is high soil moisture, plants become too tall for the pegs to penetrate the soil. Since the pod growth has to occur within the soil, the number of flowers becoming pods and hence the fraction of useful flowers will be smaller when there is excessive growth of plants during the flower initiation phases.

It is known that when an adverse event occurs in the first batch leading to a smaller fraction of useful flowers there is some compensation in the second batch. This effect has been incorporated in this model. Generally the useful fraction in the first batch ($p1$) is more than twice that of the second batch ($p2$). So we assume the fractions in the two batches to be $p1 = 0.7$ and $p2 = 0.3$ in the absence of any adverse events.

When an adverse event occurs in the first batch, we assume that there is some compensation in the second batch. We assume the loss due to an adverse event in the first batch to be large (about 40%) and take the useful flower fraction for the first flower fraction in this case to be $p1 = 0.4$. If full compensation was assumed then in the absence of an adverse event in the second batch, $p2$ would have been 0.6. We assume partial compensation and take $p2$ in this case to be 0.45. If an adverse event occurs in both the batches, we assume that $p2$ is further reduced and take $p1 = 0.4$ and $p2 = 0.39$.

In the model, the two batches of flower initiation are considered separately for the later developments such as pod formation, pod filling, etc.

Harvesting. Both very dry soil conditions and very wet soil conditions during harvest result in the loss of crop production. When the soil is too dry, the farmers find it difficult to pull out the groundnuts. When it is too wet, the groundnut seeds start germinating. It should be noted that the time of harvest depends on the adverse events that have occurred earlier. If there are losses of leaf area due to leaf miner or tikka, the farmers go in for an early harvest between 100 and 110 days. Otherwise they wait for another 10 days, so that pods from the second batch of flowers can mature and thereby increase the yield. Therefore, in this model the harvest date is fixed between 100 and 110 days if there are adverse weather events leading to either leaf miner or late leaf-spot attack. Otherwise the harvest date is taken as between 110 and 120 days.

Pests/diseases and weeds triggered by critical events

The indirect impact of adverse weather events by triggering some of the important pests/diseases and weeds over a period cutting across different life stages of the crop is also incorporated in the model.

Leaf miner. Leaf miner is a major pest of groundnut, causing extensive damage to the leaves. Leaf miner populations at a low level are always present in the region. When favourable weather conditions occur, the populations build up rapidly and attack the crop. The conditions favourable for the leaf miner are long dry spells resulting in high temperature and low humidity[18]. Dry conditions which can promote leaf miner growth are defined here in terms of the soil moisture. Soil moisture less than 0.5 S_a (i.e half the maximum value) is taken as an indicator of dry conditions. We define a day as a leaf-miner day if the soil is dry (S_m £ $0.5\ S_a$) and it is a non-rainy day. We use the IMD definition of non-rainy day as one with rainfall of less than 0.25 mm. We expect the leaf miner population to grow during such dry periods. However an intense shower in the initial stages of leaf miner attack results in reduction in levels of pests population and also helps the plant to recover from pest damage and moisture stress. Such a wet spell is referred to as a drenching shower. In this model, rainfall of greater than or equal to 20 mm in a single day, within the first 14 leaf miner days (i.e. when a substantive fraction is at a larval stage) is taken as a drenching shower. If there are more than 21 leaf miner days (not necessarily consecutive) between 35 and 110 days after sowing, and if there is no drenching shower within the first 14 leaf miner days, then a leaf miner attack is assumed to have been triggered (Figure 9). The loss in yield due to an attack by the leaf miner can be up to 40%. The loss in a particular year is estimated as follows. If there is a drenching shower within the first 14 leaf miner days (Figure 10) we assume that, there is no attack and hence no loss. The loss is assumed to increase from 10% for 25 leaf miner days to 40% for 75 leaf miner days (Table 2).

Late leaf-spot or tikka. Late leaf-spot or tikka is a major disease of groundnut causing considerable yield loss. Late leaf-spot or tikka, stem rot and root rot are triggered by intense wet spells[19] during the period 75 to 110 days after sowing. In the model, the loss for a particular year is calculated as follows. For each set of 3 consecutive days of wet soil, the loss is taken to be 5%, up to a maximum of 20%. In other words, even if there are more than 4 sets of 3 consecutive days of wet soil, only 20% loss is assumed. If in addition, there are ten or more days of wet soil (i.e. apart from the set of consecutive wet days) an additional loss of 5% is assumed.

Weed growth. Generally farmers of the region remove weeds only once around 35 days after sowing. Therefore, weed growth during 35 to 80 days after sowing can have an impact on the yield. Weed growth is promoted

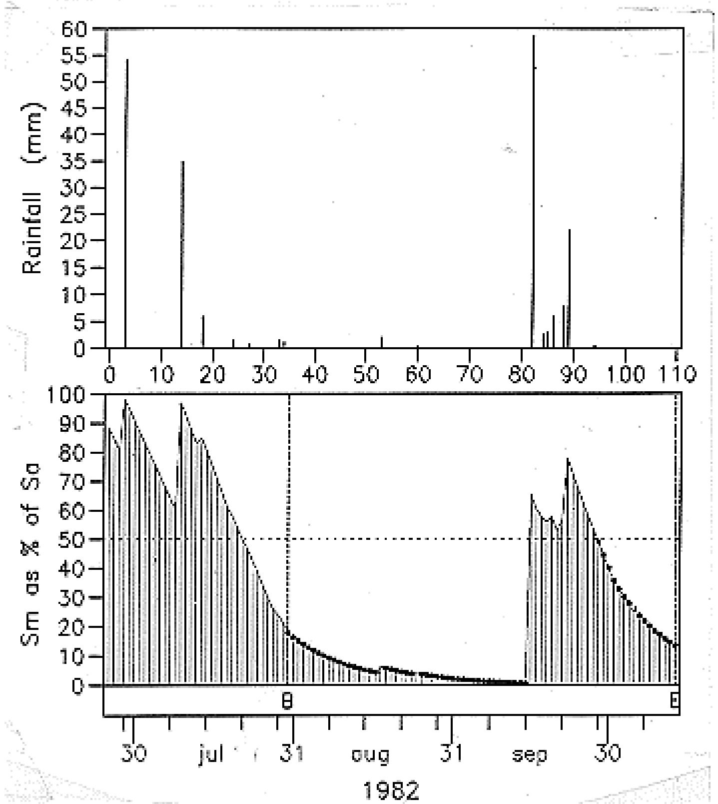

Figure 9. Variation of rainfall and simulated soil moisture during 1982 indicating the leaf miner days (indicated by solid circles between B and E).

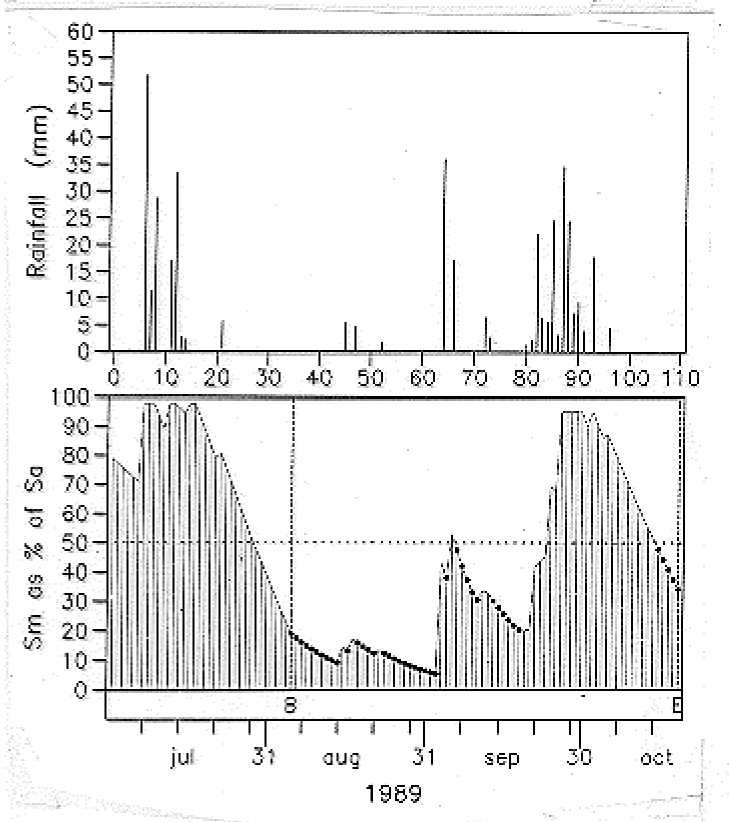

Figure 9. Variation of rainfall and simulated soil moisture during 1982 indicating the leaf miner days (indicated by solid circles between B and E).

Figure 10. Variation of rainfall and simulated soil moisture during 1989 indicating leaf miner days and the drenching shower in early September.

by wet spells. In this model, if the soil is too wet for any 7 consecutive days or rather wet for any 14 days (Table 2) weed growth is assumed to take place. The yield loss associated with weed growth is taken as 10%.

Simulations with the heuristic model

Simulation of the heuristic model was carried out using the rainfall data for the Anantapur meteorological station during 1911–1990. The probabilities of the triggering of the different pests/diseases and weeds are given in Table 3.

As expected for this semi-arid/arid region, the probability of leaf miner attack which is triggered by dry spells, is very high. We found that the threshold of the number of dry days, conducive for the leaf miner attack was crossed in over 93% of the years. However, in about a third of them drenching shower occurred, preventing the growth of the leaf miner. In spite of the average rainfall being rather low, we note that the probability of the diseases promoted by wet spells is also large. For late leaf-spot, it is over 52% while for seed rot it is 25%. This brings out clearly the importance of the distribution of rainfall within the season in determining the nature of the impact of climate. It is seen that the impact of wet spells on flower initiation is also large. Further results such as the probability of leaf miner for a given sowing date, or given the rainfall until that time, can be readily computed from this model. However we believe that it is necessary to validate the model before elaborate conclusions are drawn.

Validation

The validation can occur at two levels. Firstly, the assumptions of the model in terms of the conditions for land preparation and the criteria for triggering pests and diseases need to be validated. This can be done by comparison of the sowing date and incidence of pests/
diseases with the available observations at the agricultural station. Secondly, whether the year-to-year variation of the total loss simulated by the model corresponds to the observations at district and larger spatial scales

Table 3. Anantapur, 1911–1990 and sample, 71 years

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Adverse events triggering	Probability
Seed rot	0.25
Losses during flower initiation	0.44
Difficulty in harvest due to dry spell	0.51
Difficulty in harvest due to wet spell	0.32
Leaf miner	0.65
Late leaf-spot (tikka)	0.52
Weed growth	0.31

Table 4. Comparison of observed and simulated sowing date

Table 5. Incidence of leaf miner Infestation of tikka

Table 4. Comparison of observed and simulated sowing date

Year	Sowing date at agricultural station	Sowing date in the model	Remarks
1975	27 July	1 August	
1976	9 August	abandoned	
1977	11 August	28 July	Second sowing opportunity used at the agri station
1978	10 August	10 August	
1979	31 July	3 August	
1980	14 August	abandoned	
1982	30 June	25 June	
1983	5 August	5 July	Second sowing opportunity used at the agri station
1984	12 July	18 July	
1987	4 August	9 July	
1988	29 June	25 June	

Table 5.

Year	Incidence of leaf miner		Infestation of tikka	
		Model		Model
1975	No	No	No	Yes[2]
1976	Yes	Abandoned	No	Abandoned
1977	Yes	No[1]	No	No
1978	Yes	Yes	Yes	Yes
1979	No	Yes	No	No
1980	Yes	Abandoned	No	Abandoned
1982	Yes	Yes	No	No
1983	No	No	Yes	Yes
1984	Yes	Yes	No	No
1987	No	No	No	No
1988	No	No	Yes[3]	No

[1]Sowing dates differ by 44 days and drenching shower in the model.
[2]Mild attack observed with 10% loss.
[3]Tikka was noticed at 55 days (i.e. well before the 75–110 days assumed in the model).

has to be ascertained. We address the latter aspect later in the article.

We compared the observed sowing date and the incidence/infestation of leaf miner and late leaf-spot or tikka at Anantapur agricultural station with those simulated by the heuristic model run for the rainfall data at the Anantapur agricultural station. The sowing dates and the incidence of leaf miner and late leaf-spot at Anantapur agricultural station and in the simulation of the heuristic model for the few years for which observations were available are shown in Tables 4 and 5.

It is seen from Table 4 that the sowing date in the model is within a few days of the sowing date at the agricultural station except in 1977, ’83 and ’87. In each of these three years the second sowing opportunity was taken at the station. Thus the criteria used for determining the sowing date appear to be reasonable. We will not investigate the impact of using other sowing opportunities in this paper.

Comparison of the incidence of leaf miner (Table 5) shows that out of nine cases, in seven there is agreement between the model and observation. In 1977, when leaf miner attack occurred but was not simulated, the sowing date in the model is 44 days earlier and a drenching shower on 10 August (i.e. a day before the sowing at the station) killed the leaf miner in the model. This suggests that early sowing helped to avoid attack by leaf miner during that year.

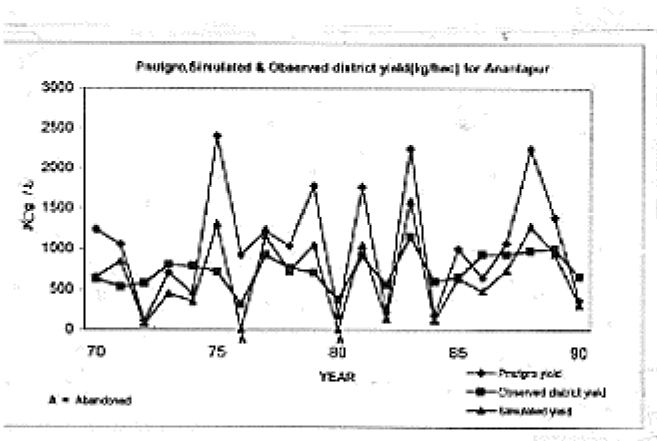
In the case of late leaf-spot again, in seven years out of nine there is agreement (Table 5). In 1988, when the incidence occurred only at the station, it was reported to have occurred at 55 days after sowing, whereas in our study we have assumed that it cannot occur before 75 days on the basis of existing literature and experience.

This comparison of sowing dates and the incidence of leaf miner and late leaf-spot suggests that on whole the model seems to be performing reasonably well. More systematic validation programmes will be undertaken this season. The criteria used for land preparation operations as well as triggering of pests/diseases/weeds in terms of soil moisture will be validated by systematic observations of soil moisture in the fields. This may lead to some modification and also suggest some changes in the criteria for different soil/topographic situations.

Simulation of the total impact

The PNUTGRO model was run for the period 1970–1990 with the sowing date in each year specified as that determined from the heuristic model. Since the PNUTGRO model simulates well the year-to-year variation in yield at the agricultural station where pests/
diseases are absent (Figure 4), we take the PNUTGRO yield for each year as the yield that would have been obtained in the absence of pests/diseases. The losses that occur in any year due to pests and diseases are estimated from the heuristic model simulation for the specific year. Thus by using the PNUTGRO model in conjunction with the heuristic model, the yield in any given year can be simulated. The PNUTGRO yield, the simulated yield (using PNUTGRO in conjunction with the heuristic model) and the observed district average yield for 1970–90 are shown in Figure 11.

The farmers get no profit at all when the yield is below 500 kg/ha. Hence yield below this level implies crop failure. Note that the two years for which the simulation of the heuristic model suggested that sowing would be abandoned (1976 and 1980), are characterized by failure of the crop with the observed yield being 310 kg/ha and 370 kg/ha, respectively. In general, when the yield is low, the potential and district yields are close. We note that in some years with very low yield (1972, ’80, ’82, ’84 and ’90) the district yield is slightly higher than the potential yield, perhaps because the



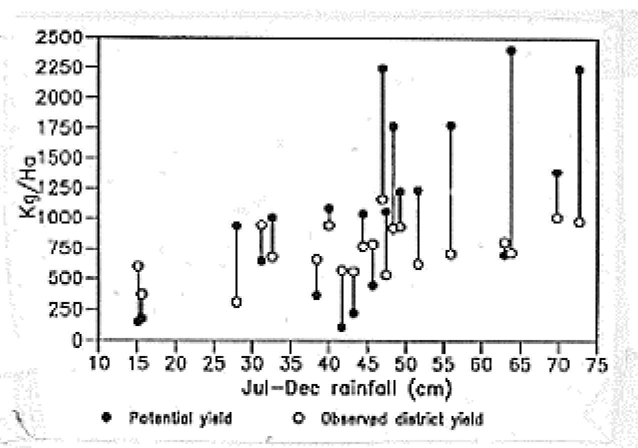


Figure 11. Variation of the PNUTGRO yield, the simulated yield (using PNUTGRO in conjunction with the heuristic model) and the observed district yield during 1970–90.

Figure 12. Variation of the simulated yield from the PNUTGRO model and the observed district yield with July–December rainfall during 1970–1990.

PNUTGRO model overestimates the impact of moisture stress on the yield of this variety of groundnut. In any event, it is clear that the yield gap is rather small in such years suggesting that the farmers are able to get close to the best possible yields under these unfavourable circumstances. If a seasonal prediction of rainfall was sufficiently accurate to provide reliable predictions of such low yields, the farmer has to either minimize investments in the crop or change the cropping pattern.

It is seen from Figure 11 that for several years (e.g. 1975, ’79, ’83 and ’88), with a large gap of over 1000 kg/ha between the PNUTGRO yield and actual yield, a large fraction of the yield gap can be attributed to yield-reducing factors (pests/diseases/weeds) incorporated in the heuristic model. In spite of not including the possibility of the farmers using second or later sowing windows, it is found that the observed and simulated values of yield are rather close suggesting that the heuristic model in conjunction with PNUTGRO can be used for assessment of the impact of climate.

The variation of potential and district yield with the July–December rainfall is shown in Figure 12. It is seen that there is a sharp change in the potential yield with seasonal rainfall of about 45 cm. When the rainfall is less than this threshold, the maximum potential yield is about 1000 kg/ha; whereas above this threshold it can be around 2000 kg/ha or more. Even when the rainfall is above the threshold, there are large variations in the potential yield. For example during the year 1973 and 1975, the seasonal (July–December) rainfall was 63 cm and 63.8 cm respectively and yet the potential yield was 703 kg/ha and 2407 kg/ha, respectively. The impact of the nature of distribution of the rainfall within a season (Figure 2) is seen with the year 1975 having well distributed rainfall characterized by three times of the potential yield of 1973. This demonstrates very clearly that the seasonal rainfall as well as the distribution within the season are important in determining the yield. Thus using these models considerable insight can be gained into the nature of the impact of climate and when they are improved sufficiently to simulate the observed variations of yield, the yield for a given distribution of rainfall can be estimated with some degree of confidence.

Concluding remarks

We expect that development of models for the indirect impact of climate variability (e.g. heuristic model discussed here) and a model for the total impact (e.g. heuristic model in conjunction with PNUTGRO) will be useful in decision support systems. There are two kinds of decisions for which the analysis presented here could be useful. The first is concerned with management options after a specific variety is sown, while the second, with the choice of the sowing date and/or variety. In the first category there are options such as the choice of the strategy (e.g. to spray or not to spray pesticides). The important factors in this decision are the cost of the remedial measure and expected loss in case of infestation. On the basis of probabilities of the attack of certain pests/diseases estimated by the heuristic model, the cost/benefit of each of the two strategies can be estimated and hence a decision about spraying pesticides could be taken objectively[20]. For example we find that that the probability of a dry spell which promotes leaf miner over this region is above 93%. In about 30% of such years, a drenching shower occurs, implying that no spraying is necessary. Hence once leaf miner populations have started growing, the probability that a pesticide will be useful is 63%. This information could be used in deciding the optimum strategy. The optimum strategy may involve spraying as soon as the leaf miner populations cross the threshold or a 'wait and see' strategy depending on the climatic variability of the region[21]. Of course, if in any given year, a prediction of when a dry spell will end can be given with sufficient reliability[20], it will help the farmer to decide about spraying.

The second application of the present study is for tailoring crop varieties/operations to be optimal for the climate variability of the region (or the expected variability for a given year if reliable predictions are available). Such tailoring is essential in diseases such as pod-rot for which there are no remedial measures available. In fact, such tailoring may also become important for pests/diseases which require intensive spraying, because of the recent awareness of the adverse effects of pesticides on the ecology and associated restrictions on the level of pesticides allowed in grains for the internal and foreign markets. The problem of control of pests/diseases with minimum plant control chemicals, has assumed great importance even in the rice and wheat belts in the Indo-Gangetic plains where rapid increase in yields occurred with the green revolution.

For such tailoring, an easy option available to the farmer is the choice of the sowing date. Although choosing an alternative sowing date may not involve any additional costs, it could involve losses, if the farmer chooses to skip the first opportunity and the second one does not arise. It is well known that the sowing date has a significant impact on the yield. For example, Singh *et al.*[6] have shown that under biotic stress-free conditions, the simulated yield increased from 0.4 to 1.2 tons/hectare when the sowing date was changed from 12 July to 12 August in 1988. In addition, it may also be possible to choose varieties which differ in the length of the growing season. For a given variety, the choice of sowing date determines the life history stages at which the different critical events such as wet spells/dry spells occur and hence the extent of moisture and biotic stress suffered. It also determines whether wet/dry spells will occur during harvest and lead to operational difficulties.

By detailed analysis of the variation in yield with sowing dates from the climate variability of the region, it would be possible to come up with prescriptions of the optimum sowing date for the region, as well as suggestions of traits (like duration, etc.) of a variety which is best suited for the climate variability of the region.

Once the models are refined to the level at which they simulate realistically the observed variation, they can provide information which will be useful in deciding between the management options available to the farmer. The development of such models is a prerequisite to the development of a decision support system.

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