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17 1 2 3 THE FUTURE ROLE OF A CROP MODEL IN 5 LARGE AREA YIELD ESTIMATING 1/ 6 tiple. and Y. hove 7 G. F. Arkin, C. L. Wiegand and H. Huddleston^{2/} 8 9 0 10 11 12 13 14 15 16 17 18 19 20 Contribution from the Texas Agricultural Experiment Station, the 21 1/ Agricultural Research Service, and the Economics, Statistics and 22 23 Cooperative Service. Associate Professor, Texas Agricultural Experiment Station, P. O. 24 2/ Box 748, Temple, TX 76501; Soil Scientist, USDA-ARS, P. O. Box 25 267, Weslaco, TX 78596; and Principal Research Statistician, ESCS, 26 South Building, Washington, DC 20250, respectively. 27

THE FUTURE ROLE OF A CROP MODEL IN LARGE AREA YIELD ESTIMATING

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G. F. Arkin, C. L. Wiegand and H. Huddleston

Crop growth simulation models that consider the soil-plant-atmosphere 5 6 continuum have only recently been introduced as research tools. The 7 incentive to develop such models resulted from the successful modeling 8 of photosynthesis toward the end of the 1960's. Crop growth simulation 9 models for corn, cotton, alfalfa, short-grass, barley, and wheat followed 10 in the early 1970's (Table 1). As illustrated, crop growth modeling is 11 in its infancy. Crop growth models are primarily research tools; few, 12 if any, are being used in management decision making. However, accurate crop growth modeling and yield forecasting could enable improved manage-13 ment decisions. Preplant and crop season weather and growing conditions 14 can be useful in determining optimum planting date, matching crop to 15 land productivity, optimizing fertilizer application rates, scheduling 16 irrigations, planning insect control programs, and estimating harvest 17 date and crop storage and handling requirements, both nationally and 18 internationally. 19

Crop growth models may be useful to economists in cost benefit 20 analyses. Growth models permit parametric analysis of cost returns on 21 the production inputs of various management alternatives. Definition 22 of genetic characteristics of particular crops may enable plant breeders 23 to use crop growth models to estimate growth and production of various 24 genetic materials for different climatic and physiographic conditions 25 and select materials suited to a specific locale. The potential use 26 of these models as management and research tools stimulated building the 27

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Table 1. Plant or Crop Simulation Models in the Literature $\frac{3}{2}$

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CROP	AUTHOR(S)	YEAR
Alfalfa	Miles, Bula, Holt, Schreiber, et al.	1973
	Holt, Bula, Miles, Schreiber, et al.	1975
Barley	Kallis and Tooming	1974
Corn	Splinter	1973, 1974
	Russo and Knapp	1975
1	Baker and Horrocks	1976
· · · · · ·	Lemon, Stewart, and Shawcroft	1971
Cotton	Baker, Hesketh, and Duncan	1972
	Stapleton, Buxton, Watson, Molting, et al.	1973
1997 - A. C.	McKinion, Jones, and Hesketh	1975
Shortgrass prairie	Connor, Brown, and Trlica	1974
Sorghum	Arkin, Vanderlip, and Ritchie	1976
	Vanderlip and Arkin	1976
Soybeans	Curry, Baker, and Streeter	1975
Sugar beets	Fick	1971
	Fick, Loomis, and Williams	1975
Wheat	Rickman, Ramig, and Allmaras	1975
	Chin Choy, Jose, and Stone	1975
	Colwell and Suits	1975
	EarthSat	1976

3/ W. W. Hildreth, Lockheed Elec., Tech. Memo.

1 grain sorghum crop growth simulation model.

Grain sorghum is exceeded only by wheat, rice, corn and barley in 2 acreage of world crops. It is grown on all six continents in regions 3 where the average summer temperature exceeds 20°C and the frost-free season is 125 days or more. Because grain sorghum can tolerate either 5 arid or wet climates, enabling production on marginal lands, its impor-6 tance as a food and feed source is growing annually. Increased world-7 wide annual grain sorghum production and grain yields can also be 8 attributed to the development of higher yielding varieties with insect 9 and disease resistance, and to improved management practices. 10

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Grain sorghum, like corn and other grain crops, is determinate and 11 produces a genetically predetermined number of leaves on a given tiller. 12 Grain sorghum has a C_4 -dicarboxylic acid pathway of photosynthesis which 13 is believed to be an adaptation for efficient, rapid carbon fixation in 14 environments where water limits plant growth. Although usually grown as 15 an annual, sorghum will grow replacement tillers if the primary tiller 16 is removed. Thus, certain cultivars have multiple uses for grain and 17 forage. Grain sorghum growth characteristics differ little over large 18 regional areas, as a result of the relative insensitivity to photoperiod 19 and the narrow genetic base among many varieties within a particular 20 maturity class. These attributes simplify modeling sorghum growth and 21 should enable the grain sorghum model described herein to be used over 22 large areas with little alteration. 23

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THE MODEL

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2 Daily growth and development of an average grain sorghum plant in a 3 typical field stand was calculated with this model. The appearance of 4 leaves, their growth rate, and the timing of these events are growth 5 characteristics simulated in the model. Light interception, photosyn-6 thesis, respiration and water use were modeled independently and used as 7 submodels in the growth model. Daily dry matter accumulation is parti-8 tioned to the appropriate plant organs, depending on the stage of plant 9 development. The cumulative dry weight for a crop is the product of the 10 plant population and the weight of the modeled "average" plant. Likewise, 11 crop yield is the product of the plant population and the weight of the 12 modeled average plant grain weight. Most of the equations describing 13 these processes are empirically derived from field measurements.

Input data required for the sorghum growth simulation model are given in Table 2. The model operates on a daily basis, and therefore only daily climatic inputs are required. Other inputs are initialized at the outset of the modeling run. A generalized flow diagram is given in Figure 1.

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SEEDLING EMERGENCE

Seeds will imbibe water at very low soil water contents. Therefore calculated seedling emergence depends primarily on temperature. Mean air temperature is used to compute days to emergence. The threshold soil temperature, below which seedlings will not emerge, is approximately 10°C. Above this threshold sorghum seedlings will emerge when a predetermined number of heat units have accumulated, depending on sowing depth. Table 2. Input data required for sorghum growth simulation model.

Plant data

Leaf number -- total number of leaves produced

Leaf area -- maximum area of each individual leaf, cm²

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Planting data

Planting date

Plant population

Row direction

Row width

1999年,1993年1月1日,1997年(1996年),1996年(1996年),1997年(1997年)。 1997年(1993年),1997年(1997年),1997年(1997年),1997年(1997年),1997年(1997年)。

Climatic data (daily from planting to maturity)

Maximum temperature, C

Minimum temperature, C

Solar radiation, langleys per day

Rainfall, cm

Location data

Extractable soil water capacity, cm

Initial extractable soil water content, cm

Latitude

1	canopy is computed by using a modification of the Bouger-Lambert equation
2	(commonly referred to as Beer's Law).
3	
4	POTENTIAL NET PHOTOSYNTHESIS
5	Potential net photosynthesis, defined as the net CO ₂ fixed during
6	the daylight hours on a ground area basis for nonlimiting water and
7	temperature conditions, is calculated using relationships developed
8	from data obtained from a canopy gas exchange chamber and simultaneous
9	light interception measurements.
10	
11	EVAPOTRANSPIRATION
12	Potential evapotranspiration is calculated using a relationship
13	between net radiation, saturation vapor pressure, and relative humidity.
14	Potential evapotranspiration, E ₀ , is computed as:
15	
16	$E_0 = 1.28 \text{ DELTA/H}_0 (\text{DELTA + GAMMA})$
17	
18	where DELTA = slope of the saturation vapor pressure curve at mean air
19	temperature, GAMMA = constant of wet and dry bulb psychrometer equation,
20	and $H_0 =$ net radiation, cm H_20 (evaporation).
21	Evapotranspiration is calculated as the sum of transpiration and
22	soil evaporation. Transpiration, E_p , is dependent upon LAI and is
23	computed as:
24	
25	$E_{p} = 0.53 E_{0} (LAI)^{1/2}$ for LAI < 3
26	
27	except when soil moisture is limiting. Potential soil evaporation, E _{os} ,

C •

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1 is calculated by: 2 $E_{os} = E_{o}$ if LAI < 0.5 3 4 or $E_{OS} = (D + H_{OS}) / (D + T) \quad \text{if LAI} \geq 0.5$ 5 6 7 where D = DELTA/GAMMA and $H_{os} = net radiation at soil surface. Soil$ 8 evaporation is calculated from the potential and is dependent upon the 9 condition of the soil (soil moisture and stage of drying). 10 WATER AND TEMPERATURE STRESS 11 A series of efficiency functions which reflect the effects of non-12 13 optimum ambient temperature and soil water conditions on plant growth 14 are used in the model. Each efficiency parameter is a dimensionless 15 coefficient with a value from 0 to 1. The soil moisture level at which transpiration is reduced depends 16 17 on LAI and soil-water holding capacity. If extractable soil water falls 18 below this level, the coefficient of water stress becomes less than 1. 19 The water stress coefficient, Figure 2, is used to reduce transpiration 20 and net photosynthesis. 21 Figure 2 22 23 Coefficient 24 of water stress 25 26 100% 25% Available Soil Water 27

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DRY MATTER 1 Net photosynthesis computed as just described is converted to 2 dry matter using the following relationship: 3 4 $DH = \frac{12}{44} \times \frac{1}{0.4} \times p$ 5 6 7 where DM is dry matter, 12/44 is the ratio of molecular weights of C and 8 CO2 respectively, 0.4 is the proportion of the plant dry matter that is 9 carbon, and pris net photosynthesis. 10 11 PHASIC DEVELOPMENT Three stages are particularly important in determining what plant 12 13 parts are increasing in weight: growing point differentiation (GPD), 14 half bloom (HB), and physiological maturity (PM). Because leaf appearance 15 and expansion were simulated in the grain sorghum model, phasic develop-16 ment was defined with respect to the appearance of leaves. For example, 17 GPD normally occurs about midway between five leaves fully expanded and 18 flag leaf visible in the whorl. The date GPD occurs was defined as the 19 midpoint between the computed date that Teaf 5 (counting from the base) 20 reaches maximum area and the computed date that the fTag Teaf emerges. 21 22 DRY MATTER PARTITIONING Dry matter is empirically partitioned to the appropriate plant parts, 23 depending upon the development of the plant (Fig. 4). For example, the 24 plant makes much of its vegetative growth during the period from GPD to 25 Early in that period dry matter is partitioned to leaves, roots and 26 HB. Leaves have first priority; the amount of dry matter production 27 | culm.

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Figure 4

DAYS AFTER EMERGENCE

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is partitioned to roots and culm in a 0.4:0.6 ratio, with at least 20%
 of the daily dry matter production going to the roots. During the
 remaining time until half bloom, dry matter is partitioned to leaves,
 roots, culm and head. Leaves again have first priority. Remaining daily
 dry matter production is partitioned to the roots, culm and head in the
 proportions 0.20:0.45:0.35, respectively.

MODEL LIMITATIONS

Several aspects need further consideration. Timing of stages of 9 10 development and partitioning of dry weight to plant parts need to be 11 made more responsive to soil water and nutrients available to the active 12 plant roots. Both water and nitrogen stress can affect the rate of leaf 13 appearance, maturity, leaf senescence, and leaf area. Development of 14 these relationships for field-grown plants would result in improved 15 timing and partitioning simulations. Including nitrogen nutrition in 16 the model would allow its use as a management factor in modeling and 17 would enable protein content of the grain to be computed. Quantitative 18 relationships among limited available soil water and internode elongation, 19 floral abortion, and uppernode branching are important in realistically 20|modeling sorghum crop growth. These morphological aspects, although not 21 considered here, can have an immense impact under certain conditions and 22 will need to be dealt with in the future. For the model to operate 23 correctly over a wide range of plant populations, tillering must be 24 accounted for. To adequately simulate yield, two major components of 25 yield must be modeled -- seed number and the rate of grain filling.

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FORECASTING CROP GROWTH AND YIELD

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In general, regression models are being used to forecast yields. 2 3 Between-year regression models assume that the current year is part of a composite population, as were the base period years which provide 4 expressions of yield as a function of meteorological variables. These 5 6 between-year models require historical yield and weather data to develop $_{7}$ the regression equations. Within-year crop yield models, like the one to be discussed, have the advantage of providing crop yield forecasts 8 g|without the dependence on a base period. Because of limited weather and 10 yield data, a between-year model requires a minimum of five years of data collection before it can be implemented. The necessary data are 11 12 often lacking for specific locales. The within-year model permits crop 13 development and yields to be projected from any point in the growing season by using weather probability data. The weather probabilities 14 are developed from historical weather records for many crop seasons. 15 Such data can describe the probability of specific weather events (i.e., 16 1, 5, 10 consecutive rainless days anytime during the growing season). 17

In one study, crop growth and yield were simulated for 20 years 18 for six different levels of available soil water at the start of each 19 growing season; i.e., 120 seasons of simulated grain sorghum growth and 20 yield data were then available for use in the stochastic approach to 21 yield forecasting. The simulated data were used to develop a conditional 22 probability forecasting technique. Cumulative distribution functions 23 (CDF's) conditioned on leaf area and available soil water were developed 24 with the simulated crop growth data for Temple, Texas, for five dates 25 during a growing season (0, 30, 45, 60 and 75 days after emergence (DAE)). 26 These CDF's were then used to forecast grain sorghum yields for a typical 27

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1 grain sorghum crop in Temple, Texas, during the 1974 growing season. The climatological forecast sequence is presented in Table 3. The 2 $_{3}$ first forecast was made at 0 DAE for LA of 0 cm² and ASW (available soil 4 water) > 9.0 cm. LA and ASW values were obtained from the model simula-5 tion data for 1974. From the CDF's the probability was 60% that the 6 yield would lie between 4600 and 7800 kg/ha. Similarly, mean yield and $_{7}$ the 60% probability yield range were forecast on the selected dates 8 throughout the growing season through 75 DAE, when the forecasted mean g value was 4392 kg/ha and the yield modeled using only the 1974 growing 10 season weather was 3822 kg/ha. Data in Table 3 illustrate that the variance around the mean remained about the same for each forecast. 11 However, the yield associated with the 20 and 80% cumulative probability 12 and the mean value drew closer to more realistic values as the season 13 progressed until, at 75 DAE, the forecasted mean yield was essentially 14 the same as the measured yield (4398 kg/ha). 15

Because stages of development, plant organ weights including head 16 weight, and leaf number are calculated within the growth simulation model, 17 it should be possible to measure these values in the field and use them 18 in making a forecast. As the crop develops, new feedback data measured 19 in the field or measured via satellite and aircraft overflight would be 20 used in forecasts. With this method, the model could be started at any 21 time in the growing season, with measured data describing the state of 22 the crop to that point. Using generated weather data for the remainder 23 of the season, new yield probabilities can be calculated. This process 24 continues as the season progresses, continually updating or adjusting 25 the model with measured inputs and then calculating new yield probabili-26 ties which should be more accurate and have less variance than forecasts 27

DAE	GROWTH STAGE ² /	LA (cm²)	ASW (cm)	FORECASTED RANGE+ (kg ha ⁻¹)	FORECASTED MEAN (kg ha=1)
0		0	>9.0	4600-7800	6214
30	3 (GPD)	>440	>9.0	3400-7250	5580
45	4-5	>1750	>9.0	3700-7200	5441
60	6 (HB)	>2650	≤10.0	2700-6100	4406
75	7-8	>2490	<u><</u> 9.0	2800-6000	4392
 97	9 (PM)	MEASURED YIELD		4398	• = = = =
97	9 (PM)	MODELED	YIELD	3822	

1/ Variety - Big Yellow - McGregor Seed Co.

<u>2</u>/ After Vanderlip (GPD - Growing Point Differentiation, HB - Half Bloom, PM - Physiological Maturity)

+ 60% Probability

Table 3

FORECASTED, MODELED AND MEASURED GRAIN SORGHUM^{1/} YIELD - 1974

TEMPLE, TEXAS

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1 made earlier in the season. This approach enables forecasts in a real-2 time framework useful for real-time decision-making information for the 3 farmer or other user groups.

The feedback submodel for the growth simulation model was just **5** recently developed. A weather model that can be used to generate prob-6 able weather during the growing season will be used with the grain 7 sorghum model to compute realistic yield probabilities.

A sample of the use of the feedback submodel is given in Table 4. 9 At four dates, ground truth measurements were used to update the model 10 for grain sorghum growth simulation from the date of the feedback entry 11 to physiological maturity.

On June 7, for example, the following ground truth information was fed back to the model: 14 leaves full grown, LAI = 2, plant dry weight = 20.05 grams, head dry weight = 3.69 grams. The model then accurately simulated both the total plant dry weight and the head dry weight and computed the date of physiological maturity within three days of the observed event. This forecast was made one month before physiological maturity and approximately two months before harvest. LAI was always overestimated because the senescence submodel of the grain sorghum simulation model is not responsive to limited soil water conditions.

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THE HYBRID SPECTRAL-PHYSIOLOGICAL MODEL

The hybrid model combines the sorghum simulation model with spectral models that use LANDSAT multispectral scanner (MSS) data or a combination of LANDSAT and weather data for estimating plant growth parameters for updating and adjusting model computations.

Dhe of the major inputs and outputs of the sorghum simulation model

TABLE 4

BAKER LLD 1 TEMPLE, TEXAS 1976

1370	GROUND	NO	FEEDBACK			
	TRUTH	FEEDBACK	<u>5-3</u>	5-18	<u>6-7</u>	6-24
5-3 # LEAVES FULL LAI PLANT DRY WT (GM) HEAD DRY WT (GM)	8 0.83 2.36 0.00	14 3.35 16.16 2.22	8* 0.83* 2.36* 0.00*			
5-18 # LEAVES FULL LAI PLANT DRY WT HEAD DRY WT	10 1.51 6.03 0.00	14 3.16 29.94 7.05	14 3.32 14.13 1.57	10* 1.51* 6.03* 0.00*		•
6-7 # LEAVES FULL LAI PLANT DRY WT HEAD DRY WT	14 2.00 20.05 3.69		14 3.05 37.10 8.72	14 3.15 20.41 6.30	74* 2,00* 20.05* 3.69*	• • •
6-24 LAI PLANT DRY WT HEAD DRY WT	2.40 44.92 21.27		2.06 57.01 31.01	2.94 46.54 12.17	2.59 46,44 17.25	2.40* 44.92* 21.27
PHYS. MATURITY DAY LAI PLANT DRY WT HEAD DRY WT	7-13 1.40 50.70 35.70	6-3 2.95 50.05 31.93	7-4 2.75 66.52 43.92	7-20 2.65 69.40 44.34	7-10 2.43 50.04 33.05	7-10 2.25 56.99 35.00
EMERGENCE ANTHESIS	3-15 6-7	3-11 5-10	3-15* 6-2	3-15* 6-14	3-15* 6-7*	3-15* 6-7*
					5 A 4 5 4 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5	

* Feedback inputs

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is leaf area. Experience has shown that leaf area can be estimated from
 satellite data. This information could be used as feedback to upgrade
 the simulation model's prediction of crop condition or to override or
 reinitialize the simulation model.

Another important aspect of this simulation model is the require-5 6 ment for plant population input. If populations change for any reason 7 during the growing season (disease, hail, etc.), this information needs 8 to be updated in the model. Satellite data are a measure of character-9 istics associated with plant population and could provide adjustments 10 that would improve the accuracy of the simulation model yield forecasts. 11 Although the satellite data are not a measure of plant population per se 12 they respond to green biomass variation due to stand and to green leaf 13 area. The spectral data characterize fields with information that is a 14 surrogate for plant population. Satellite-obtained estimates of LAI are 15 most useful for extending the simulation model to large geographical areas and for documenting field-to-field variability. Ground verifica-16 tion or feedback data for all fields in a state might be prohibitively 17 expensive. 18

The sorghum simulation model contains a soil water balance subroutine.
Plant-stress status is determined from available soil water in the profile, which is computed daily. With this information plus information
on physiological development of the crop and yield probabilities,
information useful for on-farm management decision making can be disseminated. These farm management advisories might range from selection of
appropriate plant populations or optimal planting date to the best time
to irrigate or the amount of water to use for irrigation.

The spectral relationships can help to identify whether optimum

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seeding rates are being used, to identify plant growth stresses, to
 stratify production areas into subareas of similar soil type and farming
 practices, to provide synoptic indications of available soil moisture
 when such data are not available from ground measurements, and to docu ment vegetation cover as it relates to soil erodibility by wind or water.

6 The interdependency of the two models and their combined output is 7 illustrated in Table 5. Management decisions based on the output are 8 also listed.

9 High correlations between spectral data and plant growth parameters 10 have been obtained (Table 6). These high correlations between LANDSAT-11 derived vegetation indices or direct digital data from LANDSAT indicate 12 that spectral data could be used to estimate plant condition parameters 13 in individual fields over large areas for feedback into the sorghum plant 14 growth model. Use of the simulation model, weather probabilities, and 15 the spectral data in a complementary manner should result in improved 16 knowledge of crop growing conditions and resultant yield.

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EXTENDING THE SINGLE-PLANT, SINGLE-FIELD MODEL

TO LARGE AREA FORECASTS

By simulating single-field growth and development in an adequate 20 sample of representative fields in a large area, one should be able to 21 estimate plant growth and development in that area. The number of 22 fields (grid density) required for adequate coverage is critical. Model 23 input data requirements for simulation of growth and development at each 24 field would not normally be available and would have to be extrapolated 25 from the existing meteorological network data. The impact that extra-26 polated input data may have has yet to be assessed. 27

CROP DEVELOPMENT STAGE	YIELD LIMITING FACTORS	SPECTRAL MODEL OUTPUT	SIMULATION HODEL OUTPUT	MANAGEMENT DECISIONS
Preplant	Available water	Surface temperature as an indication of adequacy for germina- tion; moisture conditions	Initial inputs: planting configuration plant population initial moisture	Irrigate or not Fertilizer application Seeding rate Alternative crops Seeding date selection Tillage Herbicide use
Planting .	Available water	Bkgrd. (soil) Drainage Topography Variability		Varlety Seeding ra țe
Emergence	Available water N available Leaf area index Avg. weather to end of season Avg. weather to end of stage Crop status	Planted (tilled) vs non-tilled acreage	Date of emergence Available soil water Growth: leaf appearance, leaf expansion Dry matter: CO ₂ , R ₅ Partitioning: leaf, stem, roots	Irrigation scheduling Sidedressing of fertilizer
Growing Point Differentiation (GPD)	Available water N available Leaf area index Avg. weather to end of season Avg. weather to end of stage Crop status	Vigor (synoptic) Leaf area index Crop cover Green biomass Crop I.D. and hectarage estimate updates	Available soll water Growth: leaf appearance, leaf expansion Dry matter: CO ₂ , R ₅ Partitioning: leaf, stem roots, head Date of GPD	Irrigation scheduling Sidedressing of fertilizer
Half-bloom (HB)	Available water N available Leaf area index Avg. weather to end of season Avg. weather to end of stage Crop status	Vigor (synoptic) Leaf area index Grop cover Green biomass Crop I.D. and hectarage estimate updates	Available soil water Dry matter: CO ₂ , R ₅ Partitioning: leaf, stem, roots, heads Date of HB	Irrigation scheduling Harvest, transportation, storage meds prepara- tions
Physiological maturity (PM)	Storms, disease, weathering of grain	Vigor (synoptic) Green leaf area duration or senescence rate Crop cover Discrimination between confuser crops	Growth: leaf appearance, leaf expansion Dry matter: CO ₂ , R ₅ Partitioning: leaf, stem, roots, head Date of PM	Harvest date Multiple cropping Post-harvest tillage Harvest, transportation, storage factifities

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Table 5. Simulation and Spectral Model Limitations, Outputs and Decision Options.

(Table 6. Simple linear correlation coefficients between eight vegetation indices and ground truth and between individual LANDSAT digital count and ground truth for the pooled data for 5/3, 5/21, 6/8, and 6/26 from grain sorghum fields in Bell County, Texas in 1976 (n = 25) (table from reference 9).

LANDSAT	Ground Truth Information				
Vegetation	Leaf		Plant	Plant	
Indices ⁹	Area Index	BIOMASS	Height	Cover	
	Corr	elation Coeffic	ients, r		
TVI	0.836**	0.744**	0.826**	0.717**	
TVI 6	0.867**	0.778**	0.861**	0.763**	
RVI	-0.824**	-0.722**	-0.817**	-0.707**	
PVI	0.892**	0.792**	0.877**	0.786**	
PVI 6	0.916**	0.806**	0.907**	0.830*/	
DVI	0.893**	0.791**	0.877**	0.785**	
SBI	-0.441*	-0.263	-0.459*	-0.470*	
GVI	0.893**	0.800**	0.881**	0.795**	
LANDSAT		Ground Truth	Information		
MSS Bands	LAI	BIOMASS	Plant Height	Plant Cover	
MSS4	0.036	-0.142	0.061	0.130	
MSS5	-0.389	-0.447	-0.365	-0.288	
MSS6	0.795**	0.641**	0.799**	0.759**	
MSS7	0.839**	0.690**	0.837**	0.770**	

* Statistically significant at the 0.05 probability level.

** Statistically significant at the 0.01 probability level.

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9/ Refer to transformed vegetation index, ratio vegetation index, perpendicular vegetation index, difference vegetation index, soil brightness index, and green vegetation index, respectively; for details see references 8 and 9. -15-

INPUT DATA

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It may be necessary to supplement satellite data with lower altitude aircraft imagery for areas where clouds eliminate most or all of the satellite coverages during the growing season. However, the areal coverage limitations of aircraft and the difficulties in scheduling them for low cloudiness days are enormous and restrict their use in wide-area coverage.

8 The predictability of the satellite coverage schedule months in 9 advance, once it is successfully in orbit, has advantages in efficiently 10 deploying ground resources in operational systems. Data are collected 11 with the satellite system for the same time of day at each ground location 12 and with the same sensor system worldwide. Uniformity of the data sets 13 produced by this system simplify the data processing.

Aircraft scanners are available with a larger number of spectral bands than are available on spacecraft systems. The Thematic Mapper onboard the LANDSAT follow-on missions will help eliminate this disparity. Since aircraft are much closer to the earth than orbiting satellites, the data are of much higher resolution. If it is important to identify plantings as small as 1 hectare, then with current technology aircraft data must be used. But much of the production from such small plantings is consumed in subsistence economies; high-quality synoptic images that indicate the general growing conditions may be sufficient to indicate production in such areas.

The inputs from satellite and aircraft systems are about the same --25 digital magnetic tapes and color or black-and-white images. Their 26 data processing and the interpretation procedures are similar. Factors 27 dictating a choice depend on areal extent of the application, cloud -16-

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1 conditions, resolution requirement, and data system operational costs 2 per unit area.

The amounts and kinds of ground truth information needed for large 3 area yield predictions are constantly evolving. This is because ground 4 truth needs are interdependent with advances in data processing, image 5 6 enhancement and interpretation techniques, quality of crop caTendars, 7 amount of ancillary information (soil types, rainfall) available and its use, the precision with which it is known how the plant reacts to envi-8 ronmental stresses -- i.e., physiological meaningful growth models, 9 experience, interpretation keys, and other memory features. The ground 10 truth needed today may be quite different from that required next year 11 or 5 years from now, depending on advances in other areas. 12

13 Ground truth requirements are becoming more elaborate, but not 14 necessarily to improve crop identification or estimate acreage planted. 15 Rather, the impetus is to better document soil conditions and plant 16 canopy characteristics for plant simulation and bidirectional reflectance 17 models.

Ground truth can be obtained for domestic situations. It is another 18 matter to obtain ground truth for other countries. Johannsen, Baumgardner, 19 and Wiegand (unpublished manuscript for 1972 Annual Agronomy Meetings, 20 Miami, Florida) pointed out that agronomists, geographers, and hydrolo-21 22 gists use their knowledge of the relation between spectral changes and known changes to obtain specific information about areas where no ground 23 truth was taken. Thus, the experience of the users is an important 24 25 factor in defining ground truth requirements.

The mix of soil background and vegetation information in the spectra for trops, rangeland, and forest scenes has hampered extraction of the -17-

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1	vegetation information per se. Criteria have been developed for distin-					
2	guishing vegetation from the soil background. It has been shown that the					
3	LANDSAT data space can be partitioned into zones corresponding to water,					
4	cloud shadow, low-reflecting soil, medium-reflecting soil, high-reflecting					
5	soil, clouds, low vigor vegetation, medium vigor vegetation and high vigor					
6	vegetation without any <u>a priori</u> knowledge of specific ground conditions					
7	for a scene. Such interpretations will proliferate as the universality					
8	of the spectral characteristics of water, vegetation, soil, clouds, and					
9	cloud shadows, on which the approach is based, is tested and proved. As					
10	the spectral categories for soil and vegetation are calibrated against					
11	ground conditions (or as the ground conditions are calibrated against					
12	their spectra?), the need for ground truth may lessen.					
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CONCLUSION

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A model that simulates the response of plants to the soil and 2 aerial environment (physiological crop weather model) can be used in 3 combination with spectral models that document the integrated plant 4 response to improve crop yield forecasts for large areas. The 5 6 physiological model operates on a daily basis. Modeled dry matter 7 accumulation each day is apportioned to the appropriate plant organs. 8 The spectral data provide feedback to the physiological model in terms 9 of LAI or green biomass, and aid considerably in explaining field variations in stand and current or previous differences in management 10 that affect plant vigor or soil productivity. 11 The hybrid model approach will improve as the influences of weather 12 and plant stress on phasic development and yield components (seed number 13 seed size, and number of heads per unit land area) are better quantified. 14 15 16 17 18 19 20 21 22 23 24 25 26 27

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