AgRISTARS

YM-15-00403
JSC-20239

CR-NONE C.1

A Joint Program for Agriculture and Resources Inventory Surveys Through Aerospace Remote Sensing

YIELD MODEL DEVELOPMENT

January 1985

ESTIMATING SOLAR RADIATION FOR PLANT SIMULATION MODELS

E85-10089

NASA-CR-175524

Tom Hodges, Vikki French, and Sharon LeDuc

(E85-10089 NASA-CR-175524) ESTIMATING SOLAR RADIATION FOR PLANT SIMULATION MODELS (National Oceanic and Atmospheric Administration) 23 p HC A02/MF A01 CSCL 02C

N85-21751

Unclas
G3/43 00089

NASA

1. Report No.
JSC-20239; YM-15-00403

2. Government Accession No.

3. Recipient's Catalog No.

4. Title and Subtitle

Estimating Solar Radiation for Plant Simulation Models

5. Report Date
January, 1985

6. Performing Organization Code

7. Author(s)

Tom Hodges, Vikki French, and Sharon LeDuc

8. Performing Organization Report No.

9. Performing Organization Name and Address
NOAA/NESDIS/AISC
600 E. Cherry St.
Room 200
Columbia, Missouri 65201

10. Work Unit No.

11. Contract or Grant No.

12. Sponsoring Agency Name and Address
NOAA/NESDIS/AISC
600 E. Cherry St.
Room 200, Columbia, MO 65201

13. Type of Report and Period Covered
Technical Report

14. Sponsoring Agency Code

15. Supplementary Notes

16. Abstract

There is considerable interest in using plant growth simulation models for large area yield forecasting in the United States and foreign areas. These models generally require daily input values of solar radiation, temperature, and rainfall. For calibration and evaluation of these models, historical data are needed. However, historical solar data are rarely available because solar radiation has been measured at only a few locations, frequently for only limited time periods. It would be necessary to develop surrogates for the historical data values.

Five algorithms producing daily solar radiation surrogates using daily temperatures and rainfall were evaluated using measured solar radiation data for seven U.S. locations. The algorithms were compared both in terms of accuracy of daily solar radiation estimates and in terms of respon e when used in a plant growth simulation model (CERES-wheat). Requirements for accuracy of olar radiation for plant growth simulation models were discussed. One algorithm was recommended as being best suited for use in these models when neither measured nor satellite estimated solar radiation values were available.

17. Key Words (Suggested by Author(s))
Weather Simulation
Modeling
Plant Growth Modeling
Large Area Yield Forecasting

18. Distribution Statement

19. Security Classif. (of this report)
Unclassified

20. Security Classif. (of this page)
Unclassfied

21. No. of Pages

22. Price*

*For sale by the National Technical Information Service, Springfield, Virginia 22161

Estimating Solar Radiation for Plant Simulation Models[1]

by

Tom Hodges, Vikki French, and Sharon K. LeDuc[2]

1/ Supported under NOAA Grant NA-82AA-H-00011

2/ Agronomist and Statistician, resp., Atmospheric Science Department, University of Missouri-Columbia, and Statistician, Assessment and Information Services Center, National Oceanic and Atmospheric Administration, Columbia, MO.

Contribution from the Missouri Agricultural Experiment Station. Journal Series Number 9668.

INTRODUCTION

Large area yield forecasting for the United States and foreign areas is an application of plant growth simulation models with great potential. Forecasts from these models could be a powerful tool for agricultural and economic policy makers in both government and industry.

Daily solar radiation data are required in most models. Until recently, solar radiation had been measured at only a few locations around the world. Because of the lack of available data, various surrogates for measured solar radiation are being developed and tested for use in the models. Recently, satellite estimated solar radiation became available for most of the Western Hemisphere on a "real-time" basis. If satellite data can be used to produce accurate solar radiation estimates, one obstacle to using simulation models for large areas or many locations would be removed.

Calibration of a particular crop growth simulation model would be needed for area-specific factors: soil fertility, water holding capacity, varietal characteristics, fertilizer and pesticide applications, planting practices, and other management practices. This calibration also requires historical yield and meteorological data including solar radiation data for that area. Because historical solar radiation data are not generally available, a surrogate must be used. In this paper five algorithms are compared for producing solar radiation surrogates from commonly measured daily meteorological variables.

As used in this paper, a solar radiation "surrogate" will produce solar radiation data which is similar to observed data in terms of various statistical measures: similar daily mean, similar variability, etc. These surrogates are not intended to accurately predict observed data on any given day. The term "estimate" is reserved for accurate daily predictions, and estimates of yearly yield.

SOLAR RADIATION ALGORITHMS

Five algorithms producing surrogate measures of solar radiation are compared in this study. They are referred to as CE, SR, R0, R1, and R2. The CE algorithm (Cengiz et al, 1981) was developed using data from Columbia, Missouri. It is composed of two types of functions. Location specific functions require information on latitude. Daily functions require the day of the year and daily maximum and minimum temperature (Table 1a).

The SR, R0, R1, and R2 algorithms are based on the Richardson (1981) weather simulation model (Table 1b, c, d, e). The Richardson model uses a set of location specific constants to estimate daily rainfall, solar radiation, and maximum and minimum temperature. These constants would be available only for locations in the continental United States. The solar radiation and temperature values are estimated as daily deviations from annual curves. The annual curves consist of long term average daily values. Separate curves are used for dry days and for rainy days. Rainy days are defined as those days for which rainfall has been estimated as being greater than zero. The algorithms used in this study modified Richardson's model so that observed temperatures and rainfall were used to estimate solar radiation.

The SR algorithm (Table 1b) was based only on Richardson's annual curves for normal radiation. Separate curves were used for dry days and for rainy days. There were no daily deviations from the annual curves.

To estimate daily deviations from the annual curve values for solar radiation, temperature, and precipitation, the Richardson model uses correlations, one day lag correlations and a random component. The correlations and one day lag correlations were reported to be approximately uniform for the continental U.S. (Richardson, 1981). It may be acceptable to extend these correlations to other regions. In the R0 algorithm, the actual deviations of maximum and minimum temperatures and the correlations were used to estimate the daily deviation of solar radiation (Table 1c).

The R1 and R2 algorithms also use Richardson's correlations among daily deviations of temperature and solar radiation. These correlations and the actual daily deviations of maximum and minimum temperatures are used to produce daily deviations of solar radiation in the R1 algorithms (Table 1d).

Because the daily variability of solar radiation estimated by R1 was too small, the daily deviations of S were amplified for the R2 algorithm (Table 1e). The amplification was moderate for deviations above the annual curves but greater for deviations below the annual curves. Measured data (DOE, 1979) from St. Cloud, MN; Rapid City, SD; and Glasgow, MT were used to determine the degree of this amplification. Richardson's annual mean values of solar radiation were changed by the amplification. The new "annual mean values" were approximately 5% greater than the actual values for dry days and 15% greater for rainy days.

DATA

The SOLDAY (DOE, 1979) data set encompasses the period 1952-1974. It consists of measured and rehabilitated (adjusted for known procedural and instrumental errors) daily solar radiation values and associated maximum and minimum daily temperatures and rainfall for 27 U.S.

stations. The rehabilitated solar radiation data were viewed as "ground truth" for the purposes of this study. Seven stations (Table 2) were selected to compare the five algorithms producing solar radiation surrogates for the rehabilitated solar radiation values. Three of the seven stations (St. Cloud, Rapid City, and Glasgow) had been used in the development of the R2 algorithm. Seven surrogate data sets, one for each station, were developed for comparison with ground truth (Table 2).

When the rehabilitated and simulated solar radiation values were compared over the seven stations, several things became apparent. Some of the rehabilitated solar radiation values were obviously too large (greater than 85% of solar radiation at the top of the atmosphere). The R2 and the CE algorithms also occasionally estimated excessively high values, the CE algorithm more so than R2.

The SOLDAY (DOE, 1979) data also included daily values of solar radiation at the top of the atmosphere and the percent possible transmissivity of the atmosphere for each location.

For use with the yield model, the rehabilitated solar radiation values, the R2 algorithm values, and the CE algorithm values were screened for values greater than maximum potential. This maximum was defined to be the product of percent possible atmospheric transmissivity (%T) and solar radiation at the top of the atmosphere (ETSR). Values higher than this maximum were reduced to the maximum. This screening algorithm reduced the observed solar radiation values by an average of 0.7%, the R2 algorithm values by an average of 0.5%, and the CE algorithm values by an average of 1.0%. Values from the R0, R1, and SR algorithms were not affected by the screening.

COMPARISON METHODOLOGY

The surrogates of solar radiation could themselves be compared to the rehabilitated ground truth data to determine which was the best estimate. These surrogates were developed solely for use in simulation models, however. Because of this, it was felt that their impact on yield prediction in the models would be the important criterion. The best algorithm would not necessarily be the one which produces the best estimates of ground truth but rather would be the one which produces similar yield predictions when used in a simulation model.

The Ceres-wheat model (Ritchie and Godwin, 1983; Otter, Ritchie and Godwin, 1983) was the model selected for comparison of the five solar surrogates. This program requires initial parameter values for initial soil water content, soil water retention characteristics, variety of wheat (*Triticum aestivum* L.) planting density and depth, planting date, and latitude.

Model estimates were derived using data from three of the SOLDAY stations: St. Cloud, Minnesota; Rapid City, South Dakota; and Glasgow, Montana. Both continuous cropping and summer fallowing practices were used. Median planting dates for each year at each station were estimated using a spring small grains planting date model (Hodges and Artley, 1981). Daily values of rainfall and maximum and minimum temperature were required for each station.

The solar radiation input was first supplied by the rehabilitated ground truth data. Five additional model estimates were generated with identical inputs for all variables except solar radiation. For each of these, data estimated using one of the solar radiation algorithms were used. The model was also run using unscreened values from the ground truth solar radiation and from the R2 and CE algorithms. On the average, yields were reduced by less than 1% compared to model estimates using screened data.

The resulting predicted yields using each of the solar surrogates could then be compared to yields predicted using the ground truth data. The algorithm which led to results most similar to that using ground truth data could then be determined. The sensitivity of the model to variations between the algorithms could also be studied.

For the algorithm comparison, the yearly difference (D) between ground truth yield predictions (GTY) and predictions using each surrogate (EST) would be calculated:

$$D = GTY - EST.$$

The arithmetic mean of D would indicate the bias of the yield estimates. Smaller bias measures would imply better surrogates. Bias values would be calculated for each algorithm for each station for continuous cropping and for summer fallow, a total of thirty values.

It would also be important for the root mean square error, RMSE, to be small to indicate that more estimates have a small D value than a large one. This statistic is calculated by:

$$RMSE = \sqrt{D^2/n}\ .$$

The standard deviation of the D values (SD) is also calculated. This indicates what the RMSE would be if the bias were removed.

Maximum values of D (MAX D) and minimum values of D (MIN D) would also be compared. As a final measure of the similarity between GTY and EST, the Pearson correlation coefficient, CORR, would be determined.

COMPARISON RESULTS

Statistics used for comparison of yield predictions using each of the five solar radiation surrogates are shown in Table 3. Mean and standard deviations of yield predictions using the rehabilitated solar radiation data (GT) were compared to predictions using each solar surrogate.

In half of the cases, R2 produced yield estimates most similar to those using ground truth data. SR was nearest in one third of the cases. The CE algorithm had the highest bias generally. The SR algorithm had a standard deviation of the estimates nearest to ground truth. RO was the poorest in terms of similar variation.

The RMSE values indicate that the R2 algorithm produced yield estimates which had less variation around ground truth, followed by CE. RO again was the poorest. If the bias were removed, the SD values show that the CE algorithm would have been least variable. RO was, again, the poorest. The bias, being a function of the model's sensitivity to solar radiation, would be difficult to remove.

The range of the data, shown by MAX D and MIN D, indicates that for St. Cloud, MN summer fallow, all of the algorithms except R2 produced estimates which were too low in all of the years. For other areas, the ranges are comparable.

The correlation values indicate the closest correspondence between CE yield estimates and ground truth. RO and R2 did poorest using this criterion.

Although "best" and "worst" surrogates could be detected, all were very close. Each would be acceptable in terms of the correlation of their predicted yields with those yields predicted using the rehabilitated solar radiation data. Differences between indicators for summer fallowed and continuous cropped were generally negligible.

DISCUSSION

The magnitude of day to day variability of solar radiation would be more critical than day to day accuracy. This is due to the strong effect of solar radiation on the modeled soil water balance. When ample soil moisture is available, evaporation occurs at an "energy-limited" rate proportional to the energy available from solar radiation. When the modeled water content of the soil surface is depleted more than a certain amount (U), direct evaporation of water from the profile (excluding transpiration) occurs at a rate roughly proportional to the square root of the number of days on which drying has occurred. This "time-limited" evaporation rate is generally much lower than the energy-limited evaporation rate. On rainy days, 4/5 of the rainfall is available for evaporation at the "energy-limited" rate even if the surface water depletion is greater than U. On the next dry day, moisture that has entered the profile is evaporated at the "time-limited" rate if the surface water depletion is greater than U. Consider that in a dry situation when a small amount of rainfall occurs, moderate or high solar radiation will cause near total evaporation. However, low solar radiation will allow most of the rain to enter the soil profile and be subject to "time-limited" evaporation. Thus, on two days with small amounts of rainfall, daily solar radiations of 700 and 100 langleys respectively would allow considerably more water to enter the profile than would two days of 400 langleys each.

In the Ceres-wheat model, carbon fixation is affected by solar radiation in a nonlinear fashion. For radiation amounts to 467 langleys/day of intercepted light, carbon fixation is proportional to light. At higher light intensities, no additional carbon is fixed.

Uniformly moderate solar radiation (as opposed to highly variable solar radiation) will result in more biomass accumulation, more leaf growth, more water use, and under moist conditions, higher yield. However, with dry conditions, more water stress and lower yield will result.

CONCLUSIONS

Although the differences between algorithms were small, the bias and root mean square error indicated that the R2 algorithm would be recommended as a solar radiation surrogate for use in simulation models. When used in the Ceres-wheat yield model, the R2 solar radiation surrogate produced yield predictions closest to those using ground truth solar radiation data. The CE algorithm also produced close estimates, but had a larger bias which would be difficult to remove as it is a function of the model's sensitivity to solar radiation.

The R2 algorithm would also be recommended for use [illegible] foreign areas. The location specific coefficients for the R2 algorithm can be derived from long term average monthly solar radiation values; these would be available world-wide (de Jong, 1973). Only an assumption about the average difference between solar radiation on rainy days and on dry days for a location would be needed for use of this surrogate. Because of this, the R2 algorithm would be recommended for use in areas for which neither measured nor satellite estimated solar radiation values are available.

ACKNOWLEDGEMENTS

The authors wish to express their appreciation to Dr. Clarence Sakamoto for his support and supervision. Dr. Thomas Phillips and Mr. Jim Larabee provided invaluable programming and data processing support. Ms. Rita Terry reviewed the manuscript. Ms. Sue Monteer and

Ms. Mildred Grissum typed the manuscript.

This project was funded under NOAA Grant #NA-82AA-H-00011.

References

Cengiz, H.S., J.M. Gregory, and J.L. Sebaugh. 1981. Solar radiation prediction from other climatic variables. Trans. A.S.A.E. 24(5):1269-1272.

DOE, Insolation Assessment Program. 1979. SOLDAY User's Manual. TD-9739. Daily solar radiation - Surface meteorological data.

Hodges, T. and J.A. Artley, 1981. Spring small grains planting date distribution model. AgRISTARS Technical Report, SR-L1-04032, JSC-16858.

de Jong, B. 1973. Net radiation received by a horizontal surface at the earth. Delft University Press.

Otter, S., J.T. Ritchie, and D.C. Godwin. 1983. Tests of a wheat yield model -- CERES-wheat -- in diverse environments. Agronomy Abstracts 75:15.

Richardson, C.W. 1981. Stochastic simulation of daily precipitation, temperature, and solar radiation. Water Resources Research 17(1):182-190.

Ritchie, J.T. and D.C. Godwin. 1983. CERES-wheat: A general, user-oriented wheat yield model. Agronomy Abstracts 75:15-16.

LIST OF TABLES

Table 1. Equations for Solar Radiation Simulation Algorithms

a. <u>CE Algorithm</u> (Cengiz et al, 1981)

$$\text{Solar Radiation} = 49.03 + .1 * FIS - 7.26 * DBR + .06 * FIS * DBR$$

Location specific functions:

$$S = \text{Sin}\ (\text{Latitude} * \pi/180.)$$

$$T = \text{Tan}\ (\text{Latitude} * \pi/180.)$$

$$C = \text{Cos}\ (\text{Latitude} * \pi/180.)$$

$$SLD = \text{Arcsin}\ ((.5 + .007895/C + .2168875 * T)^{1/2}) * 180./\pi$$

$$SN = \text{Sin}\ (\pi * SLD/24.)$$

$$A = (S * (46.355 * SLD - 574.3885) + 816.41 * C * SN) * (.29 * C + .52)$$

$$B = (S * (574.3885 - 1.509 * SLD) - 26.59 * (C * SN) * (.29 * C + .52))$$

Daily Functions:

$$SI = \text{Sin}\ (2\pi/365. * (\text{JULIAN DATE} + 10.5) - 1.5708)$$

$$FIS = A + B * SI$$

$$DBR = (TX - TN) * 5/9$$

b. <u>SR Algorithm</u> (Richardson, 1981)

$$\text{Solar Radiation} = RM\ (I) + AR * \cos\ (.0712 * (\text{Julian Date} - 172))$$

RM (1) = Annual mean solar radiation for dry days

RM (2) = Annual mean solar radiation for rainy days

AR = Amplitude of annual solar radiation curve

For dry days, I = 1; for rainy days, I = 2

Table 1 (continued)

c. <u>RO Algorithm</u> (largely based on Richardson, 1981)

Solar Radiation = SRL * SRSD + SRBAR

If Solar Radiation < 0.0 then Solar Radiation = 0.0

If Solar Radiation > 770. then Solar Radiation = 770.

Location specific constants:

TXM (1) and TXM (2) = mean annual maximum daily temperatures for dry days (1) and wet days (2).

ATX = Amplitude of annual curves (dry day and wet day) daily maximum temperature

CVTX = coefficient of variation of daily deviations of maximum temperature from annual curves

ACVTX = coefficients of variation of ATX

TNM = mean annual daily minimum temperature

ATN = Amplitude of annual curve of daily minimum temperature

CVTN = coefficient of variation of daily deviations of minirum temperature from annual curve

ACVTN = coefficient of variation of ATN

RM (1) and (2) = mean annual daily solar radiation for dry days (1) and rainy days (2)

AR = amplitude of annual curves of daily solar radiation

CVR (1) and (2) = coefficients of variation of daily deviations of solar radiation from annual curves for dry days (1) and for rainy days ACVR (1) and (2) = coefficients of variation of AR for dry days (1) and for wet days (2)

Table 1 (continued)

Daily functions:

SRSD = ABS (SRBAR * (CVR (I) + ACVR (I) * DR))

SRBAR = RM (I) + AR * DR

A and b are matrices (3 x 3) derived by Richardson to describe the intercorrelations between daily maximum and minimum temperatures and solar radiation in the continental United States.

I = 1 for dry days or I = 2 for rainy days

ASRL = A (3,1) * PTXL + A (3,2) * PTNL + A (3,3) * PSRL

where PTXL, PTNL, and PSRL are TXL, TNL, and SRL values from the previous day

DT = Cos (.0172 * (Julian date - 200))

DR = Cos (.0172 * (Julian date - 172))

TXBAR = TXM (I) + ATX * DT

TXSD = ABS (TSBAR * (CVTX + ACVTX * DT))

The above equations are from the Richardson (1981) weather simulation. The following five equations were developed to adapt the weather simulator to estimate only solar radiation:

SRL = ASRL + B (3,1) * TXL + B (3,2) * TNL

TXL = (TX - TXBAR)/TXSD

If TXL > 1.5 or TXL < -1.5 then TXL = 0.0

TNL = (TN - TNBAR)/TNSD

If TNL > 1.5 or TNL < -1.5 then TNL = 0.0

d. <u>R1 Algorithm</u>

Same as R0 algorithm except:

SRSD = .25 * SRBAR

TXSD = 9.

TNSD = 9.

Table 1 (continued)

R2 Algorithm

Same as RO algorithm except:

Solar Radiation = Noise * SRL * SRSD + SRBAR

SRSD = .1 * SRBAR

TXSD = 14.

TNSD = 14.

where Noise = 4.4 for SRL > 0.0 on dry days

= 11.44 for SRL $\geq$ 0.0 on rainy days

= 13.2 for SRL < 0.0 on dry days

= 34.32 for SRL $\leq$ 0.0 on rainy days

If Solar Radiation > 770.1 y/day then Solar Radiation = 770.

RM (1) and RM (2) should be approximately 5% and 15% greater than the actual annual mean daily solar radiation for dry days and rainy days respectively.

Table 2. Statistics for comparison of solar radiation estimates to ground measured solar radiation (GT)

		Dry Days						Wet Days				
	GT	CE	RO	R1	R2	SRBAR	GT	CE	RO	R1	R2	SRBAR
St. Cloud, mean	421.	376.	413.	412.	423.	412.	258.	294.	241.	242.	257.	246.
MN max	801.	801.	727.	769.	801.	663.	801.	801.	637.	584.	792.	514.
Rapid City, mean	397.	405.	402.	400.	398.	401.	309.	347.	304.	302.	309.	301.
SD max	803.	815.	724.	763.	783.	660.	801.	817.	680.	629.	816.	535.
Glasgow, mean	404.	383.	402.	398.	402.	399.	295.	301.	270.	267.	296.	268.
MT max	805.	814.	738.	755.	772.	668.	806.	814.	734.	635.	813.	544.
Atlanta, mean	449.	401.	443.	443.	452.	439.	274.	325.	250.	255.	217.	260.
GA max	767.	766.	687.	707.	761.	625.	744.	745.	537.	497.	642.	440.
Oklahoma City, mean	453.	418	442.	442.	446.	440.	288.	341.	282.	284.	291.	283.
OK max	784.	790.	716.	735.	782.	648.	778.	789.	615.	545.	779.	478.
Midland, mean	502.	492.	507.	507.	531.	494.	360.	407.	365.	361.	402.	352.
TX max	804.	804.	788.	790.	804.	693.	804.	804.	702.	621.	804.	533.
Spokane, mean	449.	420.	448.	446.	450.	446.	231.	246.	215.	215.	210.	211.
WA max	815.	816.	772.	815.	814.	695.	751.	816.	672.	640.	795.	555.

Table 3. Statistical Comparison of Yield Estimates from the CERES-Wheat Model Using the "Ground Truth" Data (GT) and Estimates Using Each of the Algorithms for Solar Radiation Surrogates in the Model

St. Cloud, MN

n = 20

	MEAN	BIAS	STD	RMSE	SD	MAX D	MIN D	CORR
Summer Fallow								
GT	3193	--	601	--	--	--	--	1.000
R0	3574	-381	625	445	237	-5	-1051	.926
R1	3591	-398	630	461	238	-40	-1084	.926
R2	3078	115	672	263	242	690	-250	.934
CE	3607	-253	629	288	142	-15	-615	.919
SR	3446	-414	587	480	248	-45	-1121	.972
Continuous Crop								
GT	3150	--	633	--	--	--	--	1.000
R0	3508	-358	704	439	262	157	-1031	.929
R1	3530	-379	708	455	258	138	-1065	.932
R2	3060	90	669	277	268	690	-372	.917
CE	3356	-206	665	293	214	358	-596	.947
SR	3532	-382	722	474	288	229	-1098	.918

Table 3 (continued)

Rapid City, SD

n = 20

	MEAN	BIAS	STD	RMSE	SD	MAX D	MIN D	CORR
Summer Fallow								
GT	2509	--	1108	--	--	--	--	1.000
R0	2441	68	1483	596	606	1532	-706	.931
R1	2455	54	1429	546	556	1347	-714	.935
R2	2451	58	1336	484	492	1303	-708	.936
CE	2472	203	1419	582	558	1340	-581	.939
SR	2306	37	1437	525	536	1344	-716	.936
Continuous Crop								
GT	1420	--	1239	--	--	--	--	1.000
R0	1329	90	1240	668	677	1653	-1732	.851
R1	1308	111	1240	676	682	1639	-1764	.848
R2	1386	34	1195	495	505	1030	-1670	.914
CE	1242	177	1186	646	635	1763	-1547	.864
SR	1319	101	1238	679	687	1590	-1779	.846

Table 3 (continued)

Glasgow, MT

n = 22

	MEAN	BIAS	STD	RMSE	SD	MAX D	MIN D	CORR
Summer Fallow								
GT	1474	--	1200	--	--	--	--	1.000
RO	1410	64	1330	416	421	1652	- 330	.950
R1	1422	53	1338	404	410	1645	- 457	.954
R2	1618	-143	1207	467	455	970	-1480	.928
CE	1403	99	1323	420	418	1358	- 749	.951
SR	1375	72	1247	410	414	1688	- 332	.942
Continuous Crop								
GT	780	--	951	--	--	--	--	1.000
RO	805	- 25	1038	275	280	591	-707	.964
R1	799	- 20	984	253	258	756	-608	.965
R2	881	-101	1038	357	350	1083	-735	.942
CE	799	- 20	1030	238	243	505	-648	.973
SR	767	13	960	223	227	679	-351	.972