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The use of the Factor Separation method for climate variable interaction studies in hydrological land surface models and crop yield models

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The Factor Separation (FS) method has been utilized in the study of the biophysical response to changes in the environment to assess the relative contribution of different atmospheric factors to the biological system. In this chapter we will discuss crop simulation and land surface model-based assessments of the sensitivity to past and future changes in climatic conditions: increasing CO_2, soil moisture, temperature and radiative conditions, and crop management procedures (irrigation). FS is applied to discern specific contributions to plant responses by single variables or combinations of environmental conditions. Our FS analysis has shown that it is important to understand that biological responses are inherently dependent on multiple variables in the natural world and should not be limited to assessments of single specific parameters.

11.1 Introduction

In this chapter we demonstrate how the FS analysis technique is a useful tool for crop–climate change (crop-clim) studies. Important interactions between the atmosphere and biophysical processes occur under land surface and atmospheric carbon dioxide (CO_2) level changes. We employ the FS technique (Stein and Alpert 1993) to investigate the direct as well as the interactive effects of soil moisture, temperature, and radiative changes on the direct effects of CO_2 doubling for different land-use/vegetation types, including agricultural production.

We present recent research using land surface and agrotechnology models that applied the FS technique to evaluate the direct and interactive effects of: (i) soil moisture changes on the biological effects of CO_2 doubling for different land-use/vegetation types (Niyogi and Xue, 2006); (ii) temperature, radiation, and

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precipitation changes on two different crops (Mera *et al.*, 2006); and (iii) differing temperature, radiation, precipitation, and irrigation procedures on soybean production at ambient and enhanced CO_2 conditions (Mera *et al.*, 2010). This work used a photosynthesis-based gas-exchange/transpiration model (GEM, Niyogi *et al.*, 2009) coupled to an atmospheric-boundary layer model (Alapaty *et al.*, 1997), and CSM-CROPGRO-Soybean and CSM-CERES-Maize crop/agrotechnology models (Jones *et al.*, 2003; Hoogenboom *et al.*, 2004).

This chapter is arranged as follows. We briefly outline the models used in the various experiments in Section 11.2. Section 11.3 details the application of FS to diagnose the response to a doubling of CO_2 in a coupled atmosphere–biosphere model. In Section 11.4 we present how FS can be used to determine the relative contributions by climate variables and their interactions to maize and soybean crops and how these interactions and contributions may change in the presence of irrigation and enhanced CO_2 conditions. In Section 11.5 we present conclusions from these studies and propose methods by which FS can enhance the study of biosphere–atmosphere interactions to improve the techniques employed and model performance.

11.1.1 Background

Recent climate projections have continued to predict increasing atmospheric CO_2 and water vapor levels along with changes in surface temperature and rainfall patterns (IPCC, 2007). Curtis and Wang (1998) performed a comprehensive meta-analysis of over 500 reports of elevated CO_2 impacts on plant response and concluded that enhanced CO_2 levels led to a significant increase in total biomass and plant net carbon assimilation rates. As summarized in Beltran-Prutzkart *et al.* (this book, Chapter 6), Eastman *et al.* (2001) developed a regional-scale sensitivity study and concluded that the land-use land-cover change (LULCC) effects are comparable or even at times outweigh the direct CO_2 impacts. The biological impacts due to CO_2 changes are important, and could be even more dominant than the direct radiative effects of CO_2 changes within the surface meteorology/regional climate change framework (Pielke *et al.* 2002).

Alteration in agricultural activity is a major driver of regional LULCC. Feedbacks that occur due to LULCC are noticed in shifts in regional climate patterns, which in turn lead to changes in the vegetation productivity and land surface feedback (Pielke *et al.*, 2002). As discussed in Foley *et al.* (2005), an increase in the human population and the demand for food and fiber has expanded the croplands, pasturelands, plantations, and urban areas in recent decades. Croplands and pastures presently occupy nearly half of the land surface and have become one of the largest land-use categories, rivaling forest cover in extent. Fall *et al.* (2010) concluded that the agricultural landscapes have contributed to regional cooling of the surface in recent decades. Global climate change is expected to increase agricultural yields in colder environments, but presents major challenges for crops grown in warmer climates or with limited water resources (Iglesias *et al.*, 1996; IPCC, 2007, Working Group II Report, p. 15; Hatfield, 2008). These assessments are based on field experiments that have analyzed effects of climate change on agricultural systems, usually using single factor approaches (Allen *et al.*, 1987, 2004; Lawlor and Mitchell, 1991; Jablonski *et al.*, 2002; Council for Agricultural Science and Techonology, 2004; Pritchard, 2005). Pielke *et al.* (2004) argue that the bidirectional effect of climate change on agriculture, and that of agricultural changes on regional climate need to be analyzed in future assessments. We show that the FS framework provides a good methodological basis for such studies.

11.2 Models

11.2.1 Coupled biosphere–atmosphere model

In the first study, we used a photosynthesis-based scheme coupled to land surface models. This approach is similar to the parameterizations and scaling discussed in SiB2 – Simple Biosphere Model, version 2 (Sellers *et al.*, 1996). The biophysical module was dynamically coupled with a prognostic soil moisture/soil temperature scheme (Noilhan and Planton, 1989), and an atmospheric boundary layer/meteorological model (Alapaty *et al.*, 1997). The transpiration/photosynthesis module is based on the Ball–Woodrow–Berry stomatal model (Ball *et al.*, 1987; Niyogi and Raman, 1997) and the Collatz *et al.* (1991, 1992) photosynthesis scheme. The stomatal conductance (g_s) (inverse of stomatal resistance, R_s) is estimated as

$$g_{\mathrm{s}} = m \cdot \frac{A_{\mathrm{n}} \cdot \mathrm{rh_s}}{C_{\mathrm{s}}} + b \tag{11.1}$$

where A_{n} is the net carbon assimilation (photosynthesis) rate, $\mathrm{rh_s}$ is the relative humidity, and C_{s} is the CO_2 concentration at the leaf surface. The terms m and b are constants based on gas-exchange considerations (Ball *et al.*, 1987) as a function of C3 or C4 vegetation and land use (Sellers *et al.*, 1996). The physiological variables such as A_{n}, C_{s}, and $\mathrm{rh_s}$ at the leaf surface are estimated using transpiration/photosynthesis relationships at the leaf scale (Niyogi *et al.*, 2009).

Photosynthesis or carbon net assimilation is calculated as the difference between gross carbon assimilation (A_{g}) and respiration (R_{d}). Gross assimilation is taken as the minimum of three rates, limited by the photosynthetic (Rubisco) enzyme efficiency (Wc), the photosynthetically active radiation (PAR) captured by the leaf (We) and the leaf capacity to transport or adopt the photosynthetic outcome (Ws).

The atmospheric core and the surface models are similar to those described in Alapaty *et al*. (1997, 2001). Some changes were made to accommodate the photosynthesis and CO_2 effects within the program and the deep soil moisture and gravitational corrections to the force-restore method following Boone *et al*. (1999) to override the Jarvis-type canopy resistance.

11.2.2 CSM-CROPGRO-Soybean and CERES-Maize

We used the Decision Support System for Agrotechnology Transfer (DSSAT) models: CSM-CROPGRO-Soybean and CSM-CERES-Maize (Jones *et al*., 2003; Hoogenboom *et al*., 2004). The models simulate potential changes in the productivity and/or vegetation feedback as a function of environmental factors. The ability of CROPGRO-Soybean (SOYGRO in Hoogenboom *et al*., 1992) and CERES-Maize (Hoogenboom *et al*., 1994) to provide information on the impact of climate on crops is well documented. Indeed, the DSSAT models have been successfully applied to the study of the impact of climate change on various regions of the world (Wolf and van Diepen, 1995: Carlson and Bruce 1996; Hansen *et al*., 1996,1999; Brown and Rosenberg, 1997; Lal *et al*., 1998; Southworth *et al*., 2000; Wang *et al*., 2001; Magrín *et al*., 2002; Wolf, 2002; Mall *et al*., 2004; Mera *et al*., 2006). A number of calibration and field validation experiments have aided such global application of the models (Boote *et al*., 1997; Allen and Boote, 2000; Alagarswamy *et al*., 2006). Following successful calibration, the analysis of climate change and related sensitivity studies for impact assessments are typically conducted. The model results are deemed realistic and representative of the environmental conditions studied. CSM-CROPGRO-Soybean is a predictive, deterministic model which simulates physical, chemical, and biological processes in the plant and its associated environment. The model simulates crop yields and related agronomic parameters and predicts primary plant processes based on weather, soil, and crop management conditions. The model is process-oriented and considers crop development, carbon balance, crop and soil nitrogen balances, and soil water balance (Boote *et al*., 1998). Crop development in the model is sensitive to temperature, photoperiod, water deficit, and nutrient stresses during various growth phases and is expressed as the physiological days per calendar day (PD d^{-1}).

The CSM-CERES-Maize (Crop Environment Resource Synthesis-Maize; Jones and Kiniry, 1986; Jones *et al*., 2003; Hoogenboom *et al*., 2004) model is also a part of the DSSAT and is a predictive, deterministic model. The model is designed to simulate corn growth, soil, water, temperature, and soil nitrogen dynamics on a field scale for one growing season, and belongs to the same DSSAT family as CSM-CROPGRO-Soybean. CSM-CERES-Maize derives daily rates of crop growth (PGR, g $plant^{-1}$ d^{-1}) as the product of light intercepted by the canopy

(IPAR, MJ plant^{-1} d^{-1}) and radiation use efficiency (RUE, g MJ^{-1}). When the crop is under environmental stress, this approach has limits in calculating photosynthesis and respiration (Lizaso *et al.*, 2005).

11.3 Application of factor separation for soil moisture and carbon dioxide effects on biological response

Niyogi and Xue (2006), utilized FS to extract the direct effect due to CO_2 change or soil moisture change alone and the interactive or indirect effects due to CO_2 and soil moisture change together. The hypothesis being tested was: the projected biophysical impacts of CO_2 changes are strongly dependent on the surface hydrological state as represented by the soil moisture conditions. Using the GEM model coupled to a PBL model, four combinations for two factors (soil moisture and CO_2) at two levels (soil moisture limiting and abundant) at present day and doubled CO_2 conditions were conducted. These experiments were performed for various land-use/land-cover conditions to extract the main effects (fCO_2 and fMoist) and their synergistic interaction (fMoist:CO_2). The FS equations were developed as:

$$\begin{aligned} f_0 &= F_0 \\ F_0 &\equiv (\mathrm{CO}_2^-,\ \mathrm{Moist}^-) \end{aligned} \tag{11.1a}$$

$$\begin{aligned} f_1 &= f_{\mathrm{CO}_2} = F_1 - F_0 \\ F_1 &\equiv (\mathrm{CO}_2^+,\ \mathrm{Moist}^-) \end{aligned} \tag{11.1b}$$

$$\begin{aligned} f_2 &= F_{\mathrm{Moist}} F_2 - F_0 \\ F_2 &\equiv (\mathrm{CO}_2^-,\ \mathrm{Moist}^+) \end{aligned} \tag{11.1c}$$

$$\begin{aligned} f_{1,2} &= f_{\mathrm{Moist:CO}_2} = F_{1,2} - (F_1 + F_2) + F_0 \\ F_{1,2} &\equiv (\mathrm{CO}_2^+,\ \mathrm{Moist}^+) \end{aligned} \tag{11.1d}$$

In the above, CO_2^+ and CO_2^- refer to the scenario with doubling (68 Pa) and the then-present-day (34 Pa) climatological values of ambient CO_2 concentrations (e.g., Houghton *et al.*, 1996); and Moist$^+$, Moist$^-$, refer to the model setup for near-field capacity, or near-wilting soil moisture, respectively, for different land-use/vegetation types.

The results indicated that each of the land-use/vegetation types was unique in terms of its biological response and characteristics, yet some broad similarities could be identified. Accordingly, the different LULC categories could be clustered into four categories: Broadleaf Trees (SiB2 Vegetation Types 1, 2, and 3), Needleleaf Trees (SiB2 Vegetation Types 4 and 5), C4 Grass (SiB2 Vegetation Type 6), and C3 Grass and Shrubs (SiB2 Vegetation Types 7, 8, and 9). The results pertaining to these four groups of vegetation changes made within the model configuration are discussed in detail in Niyogi and Xue (2006). Figure 11.1 shows an example of the analysis for Vegetation Type 1. The figure portrays the average daytime variations in the simulated evapotranspiration (Etr) and net carbon assimilation or photosynthesis (An). Soil moisture dominated the Etr changes, while the CO_2 changes had a relatively small effect. Interestingly, the CO_2 impact on the Etr increased as soil moisture became limited. Changes in the photosynthesis rates were dominated by CO_2 levels (Fig. 11.1b), with higher CO_2 leading to higher An values under abundant soil moisture availability. When soil moisture was limiting, photosynthesis rates saturated around mid-day with the dip in the An curve generally corresponding to peak radiation values.

The model results showed different responses resulting from both CO_2 and soil moisture changes. This variability in the simulated outcome is due to both the direct effect as well as the interaction of CO_2 and soil moisture changes. Figure 11.2a, b gives the relative contribution of the direct changes in CO_2 and soil moisture, and their interactive feedback on modeled Etr and An.

In the figure, the first box-plot shows the direct biophysical effect of CO_2 changes, the middle corresponds to the direct effect of soil moisture changes, and the third corresponds to the interaction between soil moisture and CO_2. For Etr, some CO_2-based modulation was evident under limited soil moisture conditions. The corresponding FS results (Fig. 11.2a) suggest that the effect of doubling the CO_2 led to a reduction in Etr as a cumulative effect (interacting with soil moisture changes). Overall, the Etr changes were dominated by soil moisture availability, but the soil moisture–CO_2 interaction was antagonistic (i.e., opposite in sign as compared to the direct effects). The combined effects of soil moisture and CO_2 changes therefore suggest an overall reduction of the combined effect due to CO_2 rise and higher soil moisture availability. Considering the An response (Fig. 11.2b), the effect of CO_2 levels on carbon assimilation is clearly demonstrated (about ten times more effective than soil moisture). Again, for this case, the interaction term is antagonistic and suggests that, for the Broadleaf Evergreen trees, the impact of soil moisture availability on the net primary productivity or evapotranspiration reduces as CO_2 levels increase. As summarized in Niyogi and Xue (2006), these FS based results are physically realistic and consistent with different observations (e.g., Owensby *et al*., 1997; Curtis and Wang, 1998).

11.4 Factor Separation for assessing climatic interactions on modeled soybean and maize yields

In Mera *et al*. (2006), the FS analysis was employed to understand the effect of individual as well as simultaneous changes in radiation (R), temperature (T), and precipitation (P) on simulated agricultural crop yields for maize and soybean.

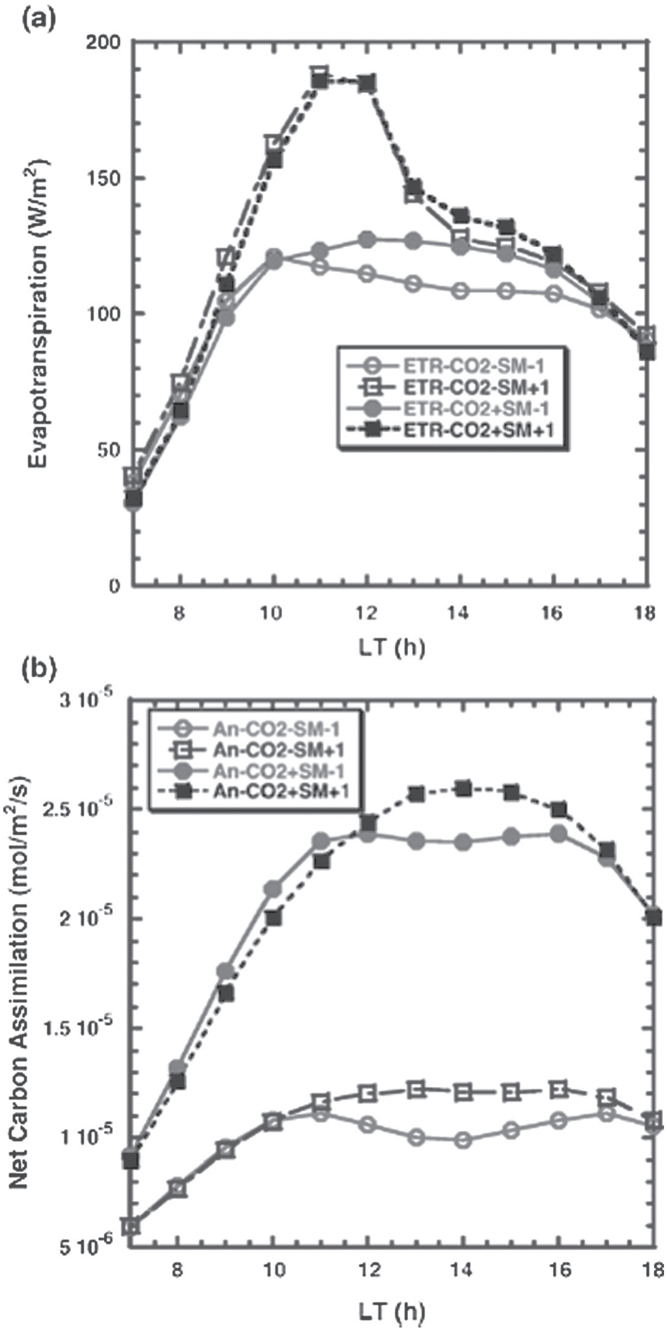

Figure 11.1 Model predicted changes in (a) evapotranspiration (Etr, W m^{-2}), and (b) net carbon assimilation (An, mol m^{-2} s^{-1}) for Vegetation Type 1 (Broadleaf-Evergreen trees). The high and low settings of the soil moisture and CO_2 values in the model initial conditions are represented by SM^+, SM^-, $CO_2{}^+$, and $CO_2{}^-$, respectively. Soil moisture has a dominant effect on Etr, while CO_2 changes are more important for An. From Niyogi and Xue (2006). See plates section for color version.

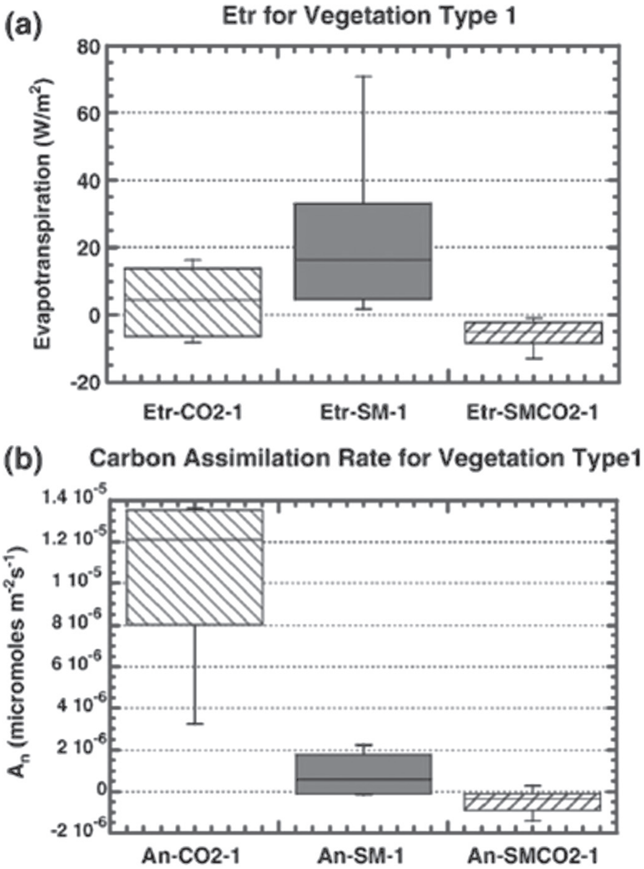

Figure 11.2 Box plots for factor-separated direct effects and interactions for (a) evapotranspiration (Etr, W m^{-2}), and (b) net carbon assimilation (An, mol $m^{-2}\,s^{-1}$) corresponding to Fig. 11.1. The SM:CO_2 term corresponds to the interaction effect. From Niyogi and Xue (2006). See plates section for color version.

Instead of eliminating or adding a factor as is generally done in the FS equations, for this study we used higher (p) and lower (m) settings of the climatic changes. Using the higher and lower values for the three variables, the eight FS equations were developed as:

$$\mathrm{E}0 = \mathrm{m}R\mathrm{m}P\mathrm{m}T \tag{11.2a}$$

$$\mathrm{E}R = \mathrm{p}R\mathrm{m}P\mathrm{m}T - \mathrm{m}R\mathrm{m}P\mathrm{m}T \tag{11.2b}$$

$$\mathrm{E}P = \mathrm{m}R\mathrm{p}P\mathrm{m}T - \mathrm{m}R\mathrm{m}P\mathrm{m}T \tag{11.2c}$$

$$\mathrm{E}T = \mathrm{m}R\mathrm{m}P\mathrm{p}T - \mathrm{m}R\mathrm{m}P\mathrm{m}T \tag{11.2d}$$

$$ERP = pRpPmT - (pRmPmT + mRpPmT + mRmPmT \tag{11.2e}$$

$$ERT = pRmPpT - (pRmPmT + mRmPpT + mRmPmT \tag{11.2f}$$

$$EPT = mRpPpT - (mRpPmT + mRmPpT + mRmPmT \tag{11.2g}$$

$$\begin{aligned} ERPT = {} & pRpPpT - (pRpPmT + pRmPpT + mRpPpT) \\ & + (pRmPmT + mRpPmT + mRmPpT) - mRmPmT) \end{aligned} \tag{11.2h}$$

The terms on the left hand side of the equation are: E0, background effect or the model results, with the smaller prescribed values (m) of the R, P, T settings. Daily meteorological observations were modified as: ±50% of observed P, ±25% of observed R, and ±2 °C of observed T to get the smaller (m) and higher (p) settings. Parameter ranges were based on summary projections from climate model results and analysis of past regional climate data for seasonal variations (Mera *et al.*, 2006).

The terms such as ER, EP, and ET are the individual contributions or the direct effect of the variable R, P, and T, respectively. Terms such as E*RP*, E*RT*, and E*PT* are the double interactions between R and P, R and T, and P and T, respectively, while E*RPT* is the triple interaction effect due to combined changes in R, P, and T. The E in the equations represents the effect. The terms m and p represent the smaller (−) and the higher (+) values of the variable from the standard design of experiment perspective (e.g., Box *et al.*, 1978; Niyogi *et al.*, 1999).

In Fig. 11.3a, b, for example, the following information is included: (a) direct effect of individual variable changes, given as ER, ET, and EP; (b) the effect of interactions between two variables (e.g., temperature and radiation changing simultaneously), given as E*RT*, E*PT*, and E*RP*; and (c) the combined effect of all three variables simultaneously affecting the crop system, given as E*RPT* (cf. Eqs. 11.2 a–h). The results in the experiment showed that different combinations of changes in climate variable lead to significantly different responses. The impact of a variable change could also depend on the values of other variables, indicating a high degree of uncertainty in the crop yield projections under climate change conditions (Niyogi *et al.*, 1999). Using FS, the different characteristics of the interactions could be extracted and can help with understanding the effect and vulnerability associated with climate change and its potential impact on crop systems.

Figure 11.3a shows the factor separation plot for the CSM-CROPGRO-Soybean simulated soybean yield for a study domain configured and calibrated using chamber-grown soybean experimental data. The double interaction of radiation and

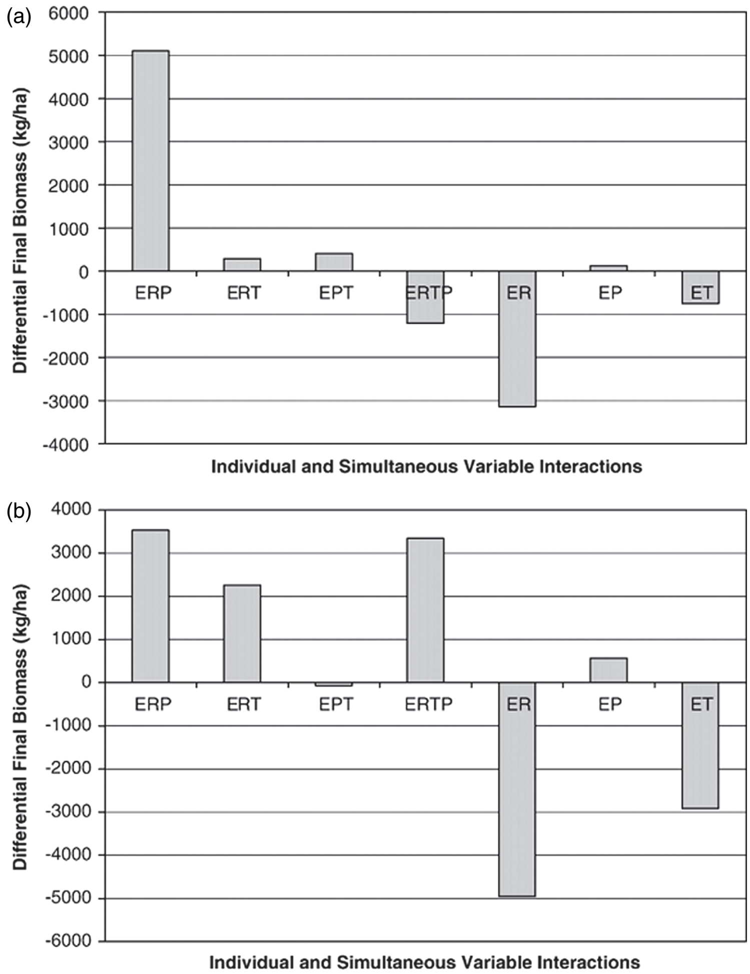

Figure 11.3 (a) Factor separation plot for soybean crop differential yield (kg ha^{-1}). A marked trend exists for the radiation–precipitation (EpRpT) interaction to have the largest positive effects. The radiation contribution (EpR) alone gives the lowest differential yield while the triple interaction (EpRpPpT) and temperature (EpT) also appear to have significant negative effects. (b) Same as (a), but for maize. From Niyogi and Xue (2006).

precipitation (E*RP*) showed the largest positive effect, suggesting that increased radiation and precipitation would synergistically impact the yield in the model projections. Double interactions between temperature and radiation (E*RT*), and temperature and precipitation (E*PT*) have relatively smaller effects. The model captures the precipitation feedback as an interaction between precipitation and radiation. The triple interaction (E*RPT*) is also significant; however, this effect is smaller than the radiation–precipitation interaction. Thus, temperature changes can antagonistically interact with the dominant radiation–precipitation interaction. In the modeled yield estimates, radiation changes (ER) can cause a significant direct effect, indicating that some reduction in radiation values could aid crop growth, and this can be further enhanced by higher precipitation and lower temperature values.

The FS analysis of the simulated maize yield is shown in Fig. 11.3b. Radiation–precipitation interaction and radiation direct effects are the dominant factors within the model. These results are similar to those obtained in the soybean studies. That is, the radiation–precipitation interaction is strongly synergistic, and the radiation direct effect is a function of a negative feedback effect. Thus, up to a certain range, decreased radiation with increased precipitation provides the highest yields. The radiation feedback is nonlinear; i.e., relatively high and very low values could reduce the yield, and with average values the yield could be high. Two differences are seen for the soybean and maize simulation results. In maize, increasing temperatures show a positive interactive effect, as compared to the negative feedback in the soybean growth model. Additionally, as compared to soybeans, maize shows prominent interactions between radiation–temperature and temperature feedback. Therefore, the temperature feedback appears to be greater for simulating maize yields as compared to that of soybeans. Thus, unlike the soybean output, the maize output indicates that all R,P,T interactions make important contributions to maize growth. Such a scenario would lead to a more uncertain output in the model projections that is less vulnerable to individual changes, but more responsive to the system as a whole.

In a subsequent experiment currently being reported in Mera *et al*. (2010), the FS analysis was extended to examine the impact of simultaneous changes in weather variables and their interactions on soybean yield under ambient and enhanced CO_2 conditions as well as irrigated and nonirrigated fields. The data collected were also validated against container-grown soybean experiments by Booker *et al*. (2005). Similarly to Mera *et al*. (2006), the direct effects of variables and their interactions were calculated as:

$$E0 = (\mathrm{m}R\mathrm{m}P\mathrm{m}T) \tag{11.3a}$$

$$\mathrm{E}R = (\mathrm{p}R\mathrm{p}P\mathrm{m}T) - \mathrm{E0} \tag{11.3b}$$

$$\mathrm{E}P = (\mathrm{m}R\mathrm{p}P\mathrm{m}T) - \mathrm{E0} \tag{11.3c}$$

$$\mathrm{E}T = (\mathrm{m}R\mathrm{m}P\mathrm{p}T) - \mathrm{E0} \tag{11.3d}$$

$$\mathrm{E}RP = (\mathrm{p}R\mathrm{p}P\mathrm{m}T) - \mathrm{E}R - \mathrm{E}P - \mathrm{E0} \tag{11.3e}$$

(a)

(b)

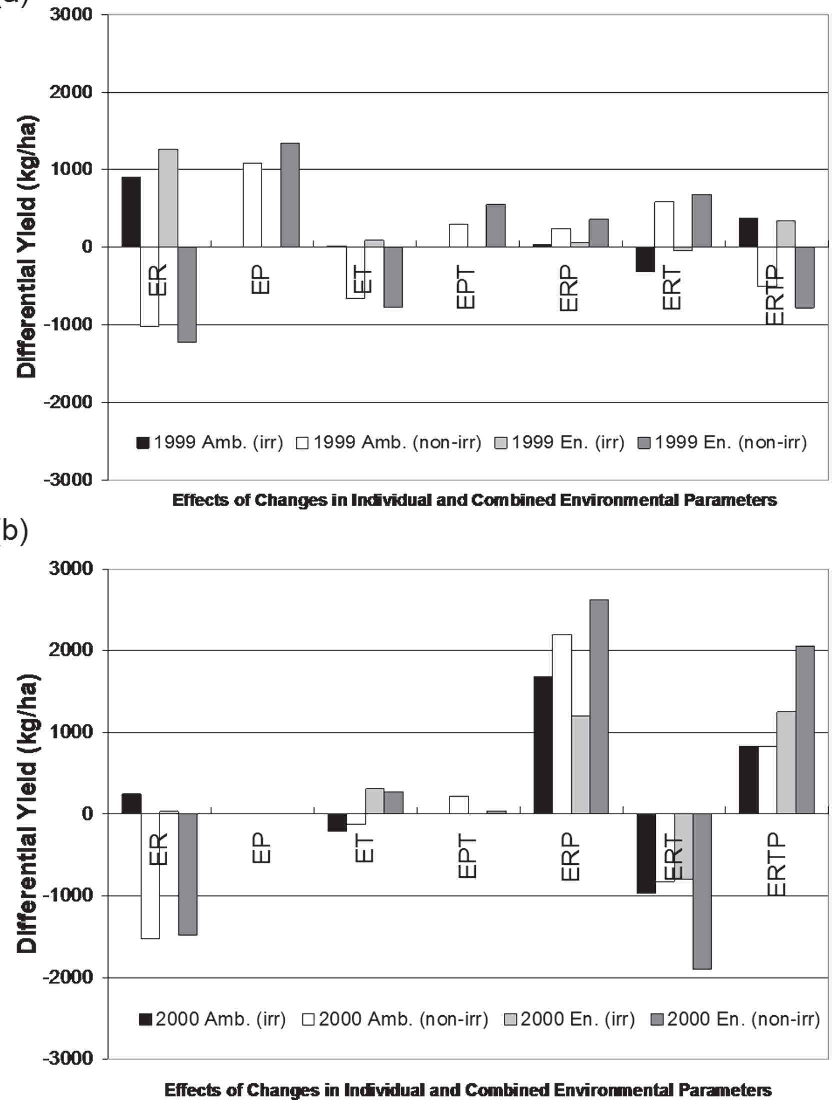

Figure 11.4 Factor separation plot for 1999 (a) and 2000 (b) soybean crop differential yield (kg ha^{-1}) Some of the main differences between the two seasons include the contributions by radiation–precipitation (E*RP*) and radiation–temperature (E*RT*) interactions. From Mera *et al*. (2010).

$$\mathrm{E}RT = (\mathrm{p}R\mathrm{m}P\mathrm{p}T) - \mathrm{E}R - \mathrm{E}T - \mathrm{E0} \tag{11.3f}$$

$$\mathrm{E}PT = (\mathrm{m}R\mathrm{p}P\mathrm{p}T) - \mathrm{E}P - \mathrm{E}T - \mathrm{E0} \tag{11.3g}$$

$$\mathrm{E}RPT = (\mathrm{p}R\mathrm{p}P\mathrm{p}T) - \mathrm{E}RP - \mathrm{E}RT - \mathrm{E}PT - \mathrm{E}R - \mathrm{E}P - \mathrm{E}T - \mathrm{E0} \tag{11.3h}$$

The higher (p) and lower (m) settings were similar to those used in Mera *et al.* (2006). Figure 11.4 shows the effect of the weather variables and their interactions on yield.

The FS analysis showed that increases in radiation (ER) positively contributed to yield under irrigated conditions at both CO_2 levels. For non-irrigated (increased water stress) conditions, there was a negative effect on yield. If soil moisture levels were adequate, an increase in radiation for enhanced CO_2 conditions increased yield in the model compared with ambient CO_2 conditions. The FS results also highlighted that the CO_2 effects are sensitive to the availability of irrigation and could be potentially used for future climate change adaption/mitigation related studies.

The FS analysis allowed us to quantify the climate–crop interactions within the crop models and to further explore their role using scenario-based assessments.

11.5 Conclusions

The examples presented in this chapter provide insights into the use of the FS approach for studying climate–crop impact assessment studies. The scope of our studies ranged from the biological response to elevated levels of CO_2 for a variety of vegetation types, to isolating the important contributions from climate variables in growth and yield simulated by soybean and maize crop models. Application of the FS technique allowed us to extract the impact of simultaneous changes to environmental variables and their interactions as well as contributions made by single variable changes. The simulations in this study showed that changes in climate variables and interactions among these factors influence the extent of the transpiration, photosynthesis, and crop yield changes associated with increased CO_2. With growing emphasis on understanding the impacts of climatic changes on food security and ecosystem services, there would be increasing utility for using FS with land surface and crop models in the future.