天氣模擬及其應用於作物生產預報
(邀請論文)

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摘　要

本文將探討天氣及作物生產預報，天氣預測之不確定性產生作物生產預報之不確定性。本文建議以整合天氣與作物模擬模式之動力與機率方法作預報。文中以堪薩斯州艾須蘭之小麥產量預報爲例。結果顯示：1.不同之天氣現象可以與預設之事件發生可能性機率之正常天氣型態一起評估。2.動力模式之使用可提供除產量外作物栽培及生長之有用資訊。3.因眞實天氣資料蒐集於生長季節及最後模擬結果必將與觀測一致，故可作進階式預報。

前　言

農業發展及系統主要決定於長期氣候。在發展一套有反應、有收穫、且有效率之農作系統時，對環境中之天氣狀況的了解，與選擇適當之作物與輪換系統之考慮，與作物栽培及病蟲害管制之實施方法是不可或缺的。相對地，生長季中之短期天氣狀況決定農業系統之實際產量。每年之產量隨天氣變化而波動。就此而論，人類歷史可視爲人在面對不定性之天氣狀況下，提高農業生產力至極限之奮鬥。歷年來，人類成功地發展微妙複雜之灌漑系統，各種具有抵抗力之作物，及其它化學及機械技術以提高農業生產力，特別是在所謂的「好」年。然而當天氣不好時，農業即遭受到不良影響。此狀況四千年前如此，在廿世紀的今天依舊如此。

本文主要討論之例子爲美國玉米產量及世界穀類生產。自 1950 年以來美國之玉米曾五度嚴重減產（圖 1.）。除了 1970 年之減產是由於玉米蟲害爆發所造成外，其它數次減產均與不良之天氣狀況有關。有三次減產發生在 1980 年代，且均因乾旱所造成。與歷年相較，1980，1983，及 1988 年之產量分別減少17%，28%及34%（Brown and Young,1988）。1988 年美國穀物總產量減少29%。這可能是美國近代史上穀物收成首次依於國內消費之記錄。因美國是最大穀物輸出國，全世界所有糧食輸入國家均感受到其減產之衝擊。的確在上述年中，世界穀物生產及消耗資料顯示糧食供應之逆差（圖 2.）。當新收成期開始時，全球糧食貯存指標爲穀類之滯銷庫存（carryover stock)，或在貯藏室之量。此量可換算成消耗相當日數。正常狀況下此日數爲60至90天。因穀物總產量減少，滯銷庫存亦減少。 1988 年之世界糧食消耗估計超出產量 152萬公噸；而滯銷庫存估計降至約54消耗相當日（圖2.）。此爲自 1960 年來最低日數。此亦少於 1972 年之57日。該年全世界穀物價格漲一倍。如果可以預測一合理期間之農產量對各國均有助益，且可發展敏銳之策略以緩和此困難。

爲預測天氣對作物生產之衝擊，我們需先預測天氣並了解天氣之變數及作物生長與產量特性間之關係。

影響長期氣候之因素

歷史上之記錄指出太陽能量之精細變化能產生對地球氣候之不敏銳作用。太陽變化性被認爲可反應太陽內部之變動。由內部亂流所造成之磁性風暴之太陽黑子被發現是以11年爲一週期（ Waldrop, 1989 ）。太陽黑子之活動增加造成全球性增溫。

另一影響地球長期氣候之因素稱「聖嬰」現象，即大氣與海洋互相作用之現象。此現象每隔 3 － 5 年發生於東太平洋；它給秘魯沙漠帶來豪雨，亦爲美國帶來溫暖的天氣。與聖嬰現象同源但較不著名的一個相反現象稱作La Niño 。它的功勞是將冷溫帶入冬季之東太平洋，並爲秘魯及智利帶來較乾之天氣，及給印度次大陸（ Subcontinent ）造成水患。上述二現象合成一稱作南振盪（ Southern Oscillation ）之巨大氣象系統之二極端。此系統之作用像一巨型之熱幫浦透過暴風雨自赤道分送能源至高緯度吹襲溫暖的西太平洋（ Linden, 1988, Rusting, 1988 ）。Handler 與Handler（ 1983 ）發現美國玉米產量與聖嬰現象之相關性。他們提出當聖嬰造成熱帶太平洋地面溫度高於正常溫度之年，美國玉米有較高之機率穫高於平均之產量。

海洋地質學家一般認爲冰河期間之長度平均爲 10000 年 ± 1000 年。Bryson（ 1975 ），聲稱我們現正處於冰河期之前夕。他指出在北極氣候已顯着變化，雲增加，且冬季降雪較多。因北極及世界其他地區之溫差驅動大氣並決定地球上之環流型態。北極之天氣變化會影響北半球之降雨型態。Bryson 預測極地氣旋之擴展會使西歐天氣乾燥；使美國之大平原帶夏季雨量減少；並會擾亂熱帶及副熱帶地區之季風系統。

不幸地，許多長期氣候現象不但無法解釋，亦無法作具高度正確性之預測。某些事件之許多基本特性或其物理機制之基礎仍是一個謎。例如：爲何太陽黑子會任意爆發？爲何太陽黑子週期爲11年而非 5 年或甚至20年？聖嬰現象與La Niño 有何關聯？

近年來，全球溫度因溫室氣體增加而上升已獲科學與政治上之相當注意。新近搜集及累積之資料顯示：因化石燃料及碳燃燒，自 1850 年以來大氣中之CO_2 濃度已增加25%。此外，甲烷（由牲口甚至稻米所產生）及其它氮氧化合物中之氟氯碳氫化合物（以造成氧氣減少而著名）之增加，有損地球之輻射平衡，並顯著地促進地球增溫效應（Kerr, 1986, Flavin, 1988 ）。此類氣體對未來之溫度及雨量之影響尚無確定性。然而，最近之全球氣候模式分析結果指出，下一個世紀中全球之地面平均溫度將增加2° － 6 °C。雖此類模式爲分析地球氣候之一些最有效的工具，但此等模式仍缺乏廣泛適用之回饋系統，如：降雪量，雲之種類，及海洋與生物對氣體增加之反應。除非各國聯合

設計一有效策略以阻止此類氣體排放進入大氣，增加之氣體將對天氣、水資源、海平面、森林、生物差異性、空氣品質、都市下部結構、人體健康及電力需求造成重大衝擊(Schneider, 1989)。

天氣及作物產量預測方法

天氣預測方法　為了解及預報以週或月為時間尺度之大氣變化，北半球(Namias 1981, Wallace 與 Gwtzler, 1981)及南半球(Mo 與 White, 1985, Treberth 與Mo, 1985)曾作過大氣遙繫及相距甚遠之點氣候參數間統計上顯著之時間相關之研究。位於科羅拉多州波德之美國國家大氣研究中心的 Harry Van Loon 及 Roland Madden 引證位於澳洲北岸之Darwin 與其他地方包括明尼蘇達州之杜魯斯間有遙繫。例如：當 Darwin 之冬季平均氣壓高於正常，則美國南部冬季溫度顯示低於正常之趨向。加州、美國中北部(包括 Dulluth)，及西加拿大之溫度有高於正常之趨向。在橫過 Caspian 海之北大西洋東部、印度、日本及西伯利亞之一部份與Darwin之氣壓有一致相關性。儘管距離大，且在中緯度自西向東移動之天氣，遙繫網路連繫赤道南振盪及偏南之天氣(Kerr, 1982)。Barnett of Scripps 研究所發現利用太平洋海平面之溫度可以早一季預測美國之氣溫。其正確性依賴季節及位置。

雖然上述之統計方法具有美學上之誘惑，但其根據刺激反應之想法不適合作延長範圍之預測。最根本的問題是氣象學家無法確定控制各種氣象現象之進化的動力機制。如果不知道這些，長期預測無科學根據作基礎，以致無法判斷數值模式之數學式是否夠完整來正確表示低頻率之氣象行為(Reinhold, 1987)。

在實際應用上，長時期預測(月或季)是根據經驗與機率的方法。美國國家氣象中心之長期預報公式為定義平均溫度或總雨量超過或少於預期之氣候之可能性的機率的敍述。此預報實際上有三步驟。首先，預報員試着以一段期間長期氣候平均之偏差來表示而預測此期間內海拔 3 公里處之平均對流層內氣流類型。第二步是由氣流類型之偏差推導氣溫之形態與降雨之差異。最後為機率之作業(Epstein, 1988)。

近年來天氣預報上多數的進展都是短期(少於 3 天)及中期(少於10天)的。Tribbia 及 Anthes (1987) 曾為文評論天氣預報所用之科學原則與計算方法。他們指出現行數值天氣模式所考慮之許多物理程序包括：凝結雲之潛熱，輻射性強之成份如 CO_2, H_2O 及 O_3 吸收及排放之輻射；雲及氣體所吸收與散射之輻射，以及地球表面之熱、溼氣、磨擦力。此外，這類模式需要分析從陸地平面站、船、海上涼台、衛星、飛機及氣球所得到之大量各種資料來提供一初始值以作為此種模式之變數。

1963 年 Edward. Lorenz 之發現粉碎了改良之數值模式有朝一日能正確地預測天氣之希望，儘管此模式與重要氣象變數有關連，並且加入複雜之物理系統。Lorenz 之結論是：天氣乃天生地難以預測。他指出可預測性之缺乏是源自對初始狀況之敏感，意

指如初始點稍作更改則數值模式之解答將完全改變（Pool，1989）。此現象現稱爲「混亂」。

然而，因混亂系統亦遵循數學邏輯，混亂下亦有其規則。混亂系統之含意有二層；其一，科學可能無法解釋某些現象；其二，世上許多複雜，看似任意之現象可能起初是單純的；而分析其複雜性可能比過去所認爲的容易。事實上，有些氣候模擬者已利用混亂原理之想法來模擬天氣現象（Vallos, 1986, Tsonis & Elsner, 1989）。

產量預測方法　對農業科學家而言，天氣預測之最終目的爲預測產量。正確之產量預測較天氣預測更難，因爲作產量預測需要知道其他知識及天氣變數與作物特性之定量函數關係。天氣一產量關係之最簡易的表示如下：

生物質量＝（用水效率）×（蒸散）

用水效率（WUE）與蒸散（T）二者均爲與遺傳及天氣有關之變數。由此基本公式可發展其他模式以闡明WUE與T，並提供有用之工具以估計特定作物之生物質量產量與天氣狀況（Noy-Meir與Harpaz 1977, Uchijima與Seino, 1985）。

然而，多數論文中檢驗天氣與作物產量關係均使用根據經驗的多重迴歸方法（如Kogan, 1985, Garcia et al, 1987, Thompson, 1988）。有些迴歸模式爲數個次迴歸模式所整合而成，其中每一個皆被設計爲作物發育中（Feyerherm & Paulsen, 1981, 1986）或某一特定生長期中（Michaels, 1978）之一項生物氣候階段。此爲歸納模式，此模式根據觀測而不需定義模式中所含變數的因果效應。因此種模式缺乏生物及物理解釋，它們常被批評無法提供與所探討現象有關之科學想法，並且其解釋之範圍與外差力均十分有限。

由於對植物生命之了解與可用之強力微電腦之普及，根據模式解以分析農業系統與預測作物生產之模擬方法亦廣爲採用。此種模式必須考慮生理學程序；如：光合作用、呼吸、蒸散、同化分離與生物氣候發展（De Wit, 1965, De Wit et al. 1978, Loomis et al. 1979）。Penning de Vries與van Laav（1982）將荷蘭科學家所作之植物模擬的進步狀況作成文獻。Wisler et al.（1986）曾發表一篇評論有關農業經營所發展之作物模擬模式，與一篇摘要。從Baier（1973），Arkis et al.（1980）與更新近之Algozin et al.（1980）之研究中可以看到用作物模擬模式應用於產量預測之例子。

以下章節，將敘述進行作物產量預測之整合模擬方法。

整合模擬方法

此整合模擬方法包括下列步驟：

1.選擇作物生長與發展模式。

2.選擇能夠產生某地之代表性天氣形態與年變化之天氣資料發生器。

3.經由天氣發生器作出一百年之天氣資料與作物模式而產生一百年之產量資料。

4.從產量與天氣之分佈，評估極端事件如乾、溼年及其產量之可能性。

5.根據預設之機率選擇乾、溼年事件。

6.極端年份（具特定機率）與平均年事件提供預測應用上的三個可能現象。

下列之小麥產量預報例子圖示此法。

作物模式 雖然爲稻米及小麥而發展之模式很多，我們將採CERES-Wheat 模式（Ritchie與Otter, 1985 ）。此模式用於美國大平原帶之冬季及春季小麥生產已經廣泛地確認（Larsen, 1985 ）。此模式之例行程序包括：受遺傳與天氣變數影響之氣象發展或生長期之天數；生物質量生產與分配，土壤水分與養分之吸收季的分析。CERES-Wheat 模式需下列資料輸入：每日之太陽輻射量，最低與最高溫，雨量，土壤排水，流失，蒸散，及輻射反應係數，土壤水分與氮剖面；產地之緯度，發展階段所需之遺傳係數與熱時間；植物密度，栽種日期，灌溉，與氮肥料之管理資料。

天氣模式 天氣模擬模式可以與作物及病害模式一併使用以評估天氣對作物產量之影響。但多數天氣模式需要長期歷史性之每日天氣資料以評估模式之參考。模式之適用性被此需求所嚴厲限制。Geng et al.（1986, 1987, 1988 ）已發展了定名爲SIMMETEO 之電腦模擬程式。此模式可根據這些變數之每月平均之長期資料產生每日天氣參數，如：雨量，最高最低溫，太陽輻射總量，平均溼度，與平均風速。此模式已在各地試測，包括Los Banos，菲律賓，Wageningen，荷蘭，與美國一些地方。表1.顯示美國大平原帶七州，14個地點所得之模擬結果。

資料選擇 我們專注於一地，即堪薩斯州之艾須蘭（Ashland），以達說明之目的。由SIMMETEO程式讀入所有相關之氣象變數之每月平均，而產生一百年之天氣資料。圖3.b 表示所模擬之一百年資料中的年雨量分佈。根據正常雨量分佈，可決定年雨量之2.5％上限與2.5％下限。雨量之分開點提供乾、溼年之狀況。以此狀況產生一百個溼年及一百個乾年之天氣資料。圖3a 與 3C分別爲乾、溼年雨量之分佈情況。再計算出這些年中每年生長季之雨量。其相對之乾、正常、與溼年之分佈顯示在圖4。這些所模擬出之天氣資料將用作小麥模式之輸入資料以產生生物質量產量曲綫。

CERES-Wheat模式之輸入資料取自國際水準點農業技術傳送網路（IBSNAT 技術報導，No.5, 1986 ），農業技術傳送之決定支援系統（DSSAT ）。此資料包括：植物遺傳係數，及土類類型資料如：土壤剖面性質，氮平衡參數，與初始狀況。

模擬結果與討論

CERES-Wheat模式可產生溼、正常、乾狀況下一百年資料以確定生物質量與產量分佈。此三種狀況下生長季間所累積生物質量每日平均顯示於圖5.。一直到第40天三種狀況之生物質量累積非常接近。第40天後溼及正常天氣較乾燥天氣顯示較快速之生長率

。溼、正常、乾之狀況下達成熟之生物質量（ Kg／ha ）分別爲：9140, 6488, 3115 。溼年達成熟之生物質量較正常年高41％；而乾年之生物質量爲正常年之48％。如溼、正常、乾年平均穀物產量分別爲2742, 1687, 及 656 Kg／ha ，則平均收成指數分別爲0.30, 0.26, 0.21 。

根據CERES-Wheat 模式，生長季可分爲5個階段：Ⅰ. 幼苗萌發至終端小穗出現（包括冬季小麥冬眠期）；Ⅱ. 終端小穗出現至營養生長結束；Ⅲ. 營養生長結束至穗生長結束；Ⅳ. 穗生長結束至穀粒充實結束（ grain filling ）；Ⅴ. 穀粒充實結束至成熟。

選出一百年正常天氣狀況中具有平均雨量及穀物產量之作物年作爲標準年以進行穀類產量預測。選出典型之溼、正常、乾年以預測標準年之穀類產量。在生長季節中根據所得之天氣資料以最新資料作4次穀物產量預報：⑴直到第一生長階段結束（第 103天）所觀測之天氣。第 103天以後三個可能天氣狀況（溼、正常、乾）被模擬，且預測生物質量與穀物產量而完成第一次產量預測。⑵第一次資料更新與第二次產量預測——加入直到第二生長階段結束（第 126天）所觀測之天氣。第 126天以後三種可能之天氣狀況（溼、正常、乾）再次被模擬。⑶第二次資料更新與第三次產量預測——直至第三生長階段結束（第 137天）所觀測之天氣。第 137天後，三種可能之天氣狀況（溼、正常、乾）被模擬。⑷第三次天氣更新與第4次產量模擬——直至第4生長階段結束（第 146天）所觀測之天氣。第 146天後，三種可能天氣狀況被模擬。第 280天爲耕種日。所有作物模擬之成熟期爲次年第 168至 171天間。

第一次預測利用直到第一生長階段結束（第 103天）所觀測之天氣，並且模擬往後之天氣。圖6.所示爲這些模擬之結果。此三種降雨狀況造成顯着不同之生物質量與產量預報。在第 103天後所預測在溼、正常、乾之狀況下成熟累積生物質量（ Kg ／ha ）分別爲11、110、7166、3410 。所預測之穀物產量（ Kg ／ ha ）則分別爲3736, 2263及 797。標準無成熟時累積生物質量爲6510 Kg ／ ha，穀物產量爲1605 Kg／ha 。標準年穀類產量與正常年穀類產量預測差異爲658 Kg ／ha 。因爲這是成熟前68天所作之長期預測，且在多數快速營養生長發生前，所預測之穀類產量易有錯誤。然而，圖6.所示爲已知植物第一生長階段之天氣狀況所預測之總產量。

第一次天氣更新（第二次穀類預測）利用直到第二生長階段（第 126天）所觀側之天氣。在第 126天後，溼、正常、乾之狀況下成熟時所預測之生物質量分別爲 8350，6670, 及 4880 （圖7.），其所預測穀物產量（ Kg ／ha ）分別爲3249, 1748, 及 8970 。預測之正常年穀物產量與標準年穀物產量差 143 Kg ／ha。第二次預測仍是在成熟前45天所作之長期預測，最高產量（在溼狀況下）與最低產量（在乾狀況下）之範圍達2352 Kg／ha 。

第二次更新（第三次穀物預測）利用直到第三生長階段結束前（第 137天）所觀測之天氣。在第 137天後在溼、正常、乾之狀況下成熟時所預測之生物質量（ Kg ／ ha ）分別爲8290,7118, 與 5870 （圖8.）；其所預測之穀物產量（ Kg／ha ）分別爲

2934，2128，與 996。最高與最低預測產量差距為 1934 Kg／ha。正常年與標準年產量預測差距為 523 Kg／ha。此差距較前各次預測為大，此乃因在第三生長階段自標準年到正常年所增加之雨量。將用來預測之天氣與到第 137天之標準天氣合在一起造成較先前之更新與預測（268 mm）多之總生長季雨量（287 mm）。先前之預測僅利用直到第126天的觀測之天氣來預測。這突顯了考慮生長季中雨量與分佈之重要性。

第三次天氣更新（第四次穀物預測）利用直到第四生長階段（即第 146天）所觀測天氣。第 146天後，在溼、正常、乾狀況下成熟之預計生物質量（Kg／ha）分別為 6990，6490，及 6320（圖 9.），所預測穀物產量（Kg/ha）分別為 1929，1566及 1443。預測之正常年與標準年穀物產量差距僅 39 Kg／ha。最高與最低穀物產量差距為 468 Kg／ha。三次穀物產量預測（溼、正常與乾狀況下）均接近於觀測產量，即 1605 Kg／ha。

預測結果指出在穀粒充實初期（第四生長階段，成熟前23.日）及可能在營養生長結束時（第三生長階段，成熟前34日）可得可靠之穀物產量預測。第一，第二生長階段結束時，即分別在成熟前 68及 45日，之預測可提供最後產量預期降低之範圍。

USDA為美國及世界其他地區作每月、每季、及每年之穀物產量預測。USDA之預測方法被視為一典範，並為其他國際組織如聯合國所採用。這個主要根據迴歸模式之預測方法被氣候學家所批評。他們爭議USDA之預測依據為過去之產量與正常之天氣，是對未來之錯誤引導（Shapley，1976）。本文所述之預測方法減緩了USDA所用方法受到之批評。首先，各種天氣現象可以與具預設事件發生可能性機率之正常天氣狀況一起評估。其次，使用動力作物模式不僅能提供最後產量之預測，且能提供作物生長及發展之資訊。第三，動力與機率方法為可作進階及自行修正之預測程序工具。換言之，當生長季節結束，因所獲訊息較多，各種預測現象將與正確機率漸增之共同預測一致。

以上所討論之模擬及預測方法並不包括可能影響長期天氣變化之因素。要考慮這些因素之困難在於它們之作用通常小於年間存在之任意波動，如圖 3.及圖 4.所示，其中溼、正常、及乾年之分佈有大量重疊部份。換句話說，即使群體平均不同，決定某年取自何群體（溼、正常、乾）是困難的。如何有效地將未來天氣變化趨勢加入模擬的困難是未來研究的挑戰。

誌　謝

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Table 1. **Comparison of Simulated and Observed 30 Year Means of Meteorological Variables for Selected Locations in the Great Plains**

State/Location	# Wet Days		Annual Rain (in)		High Temp. (F)		Low Temp. (F)	
	sim.	obs.	sim.	obs.	sim.	obs.	sim.	obs.
Kansas								
Ashland	55	54	23.25	21.55	71.1	71.1	41.2	41.2
Syracuse	40	41	14.93	15.20	70.2	70.2	38.1	38.1
Oklahoma								
Alva	66	65	27.04	24.87	72.0	72.2	46.5	46.5
Boise City	42	42	16.38	15.84	71.5	71.6	39.5	39.6
Texas								
Borger	52	54	18.62	19.33	73.0	73.0	45.2	45.3
Haskell	55	56	24.82	24.13	76.7	76.7	50.6	50.6
Colorado								
Akron	41	42	14.56	15.66	62.7	62.5	34.8	34.8
Burlington	41	40	16.16	15.32	66.2	66.2	36.9	36.9
Nebraska								
Curtis	54	55	19.51	20.09	66.2	66.2	34.9	34.8
David City	74	74	30.22	29.18	61.6	61.9	38.2	38.7
South Dakota								
Highmore	49	49	19.15	18.33	58.1	58.1	32.4	32.4
Murdo	48	48	17.03	17.12	60.4	60.4	34.3	34.3
Montana								
Harlem	31	33	11.84	11.70	56.2	56.2	27.5	27.6
Culbertson	39	40	13.69	14.29	54.7	54.9	26.5	26.6

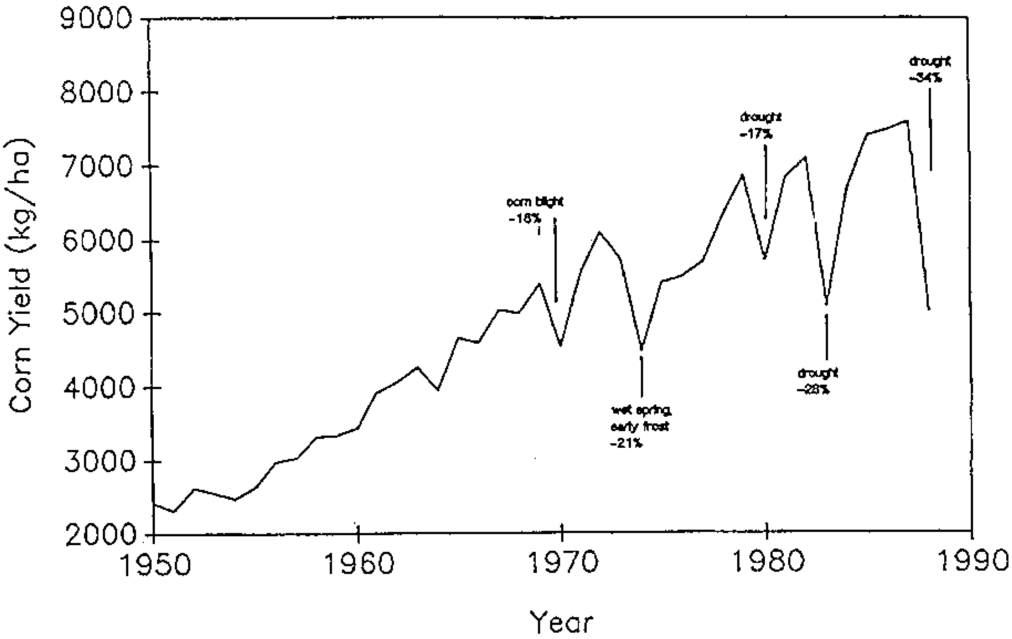

Fig. 1. U.S. corn yields per hectare, 1950–88.
(Source: U.S. Department of Agriculture. Agricultural Statistics; Brown and Young. 1988).

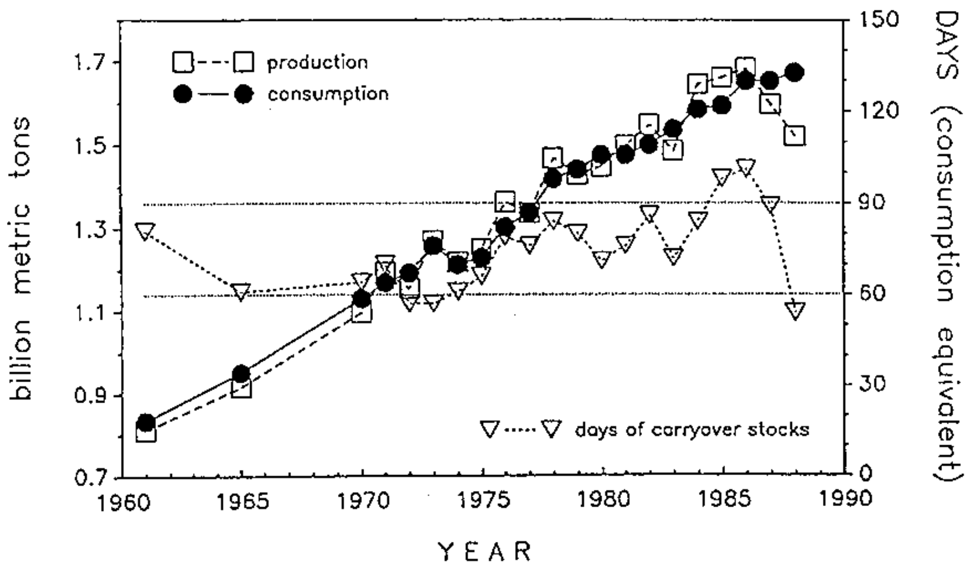

Fig 2. World grain production, consumption, and consumption equivalent days of carryover stocks.
(Source: 1961–87, U.S. Department of Agriculture, Foreign Agricultural Service, "World Grain Situation and Outlook." Washington, D.C., July 1988; 1988, Worldwatch Institute; "State of the World 1989," Worldwatch institute, p. 56).

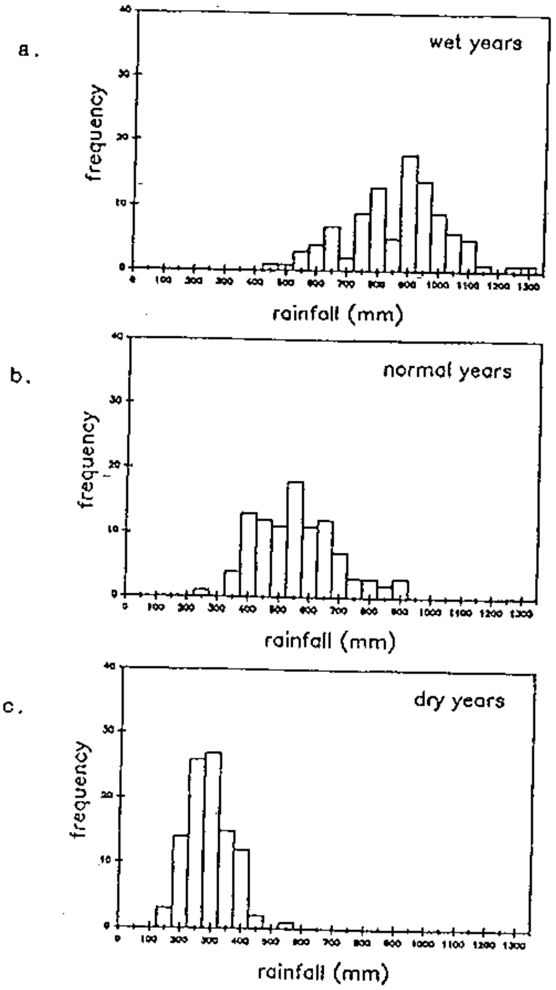

Fig. 3. 100 years of simulated rainfall totals from January to December for wet, normal and dry years at Ashland, Kansas.

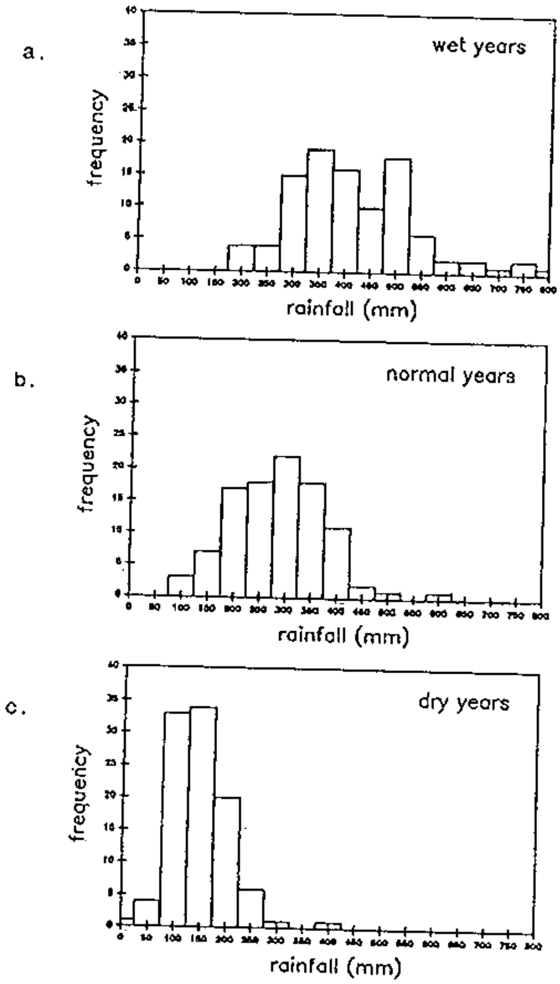

Fig. 4. 100 years of simulated rainfall totals during the growing season for wet, normal and dry years at Ashland, Kansas (Julian date 280 to 170).

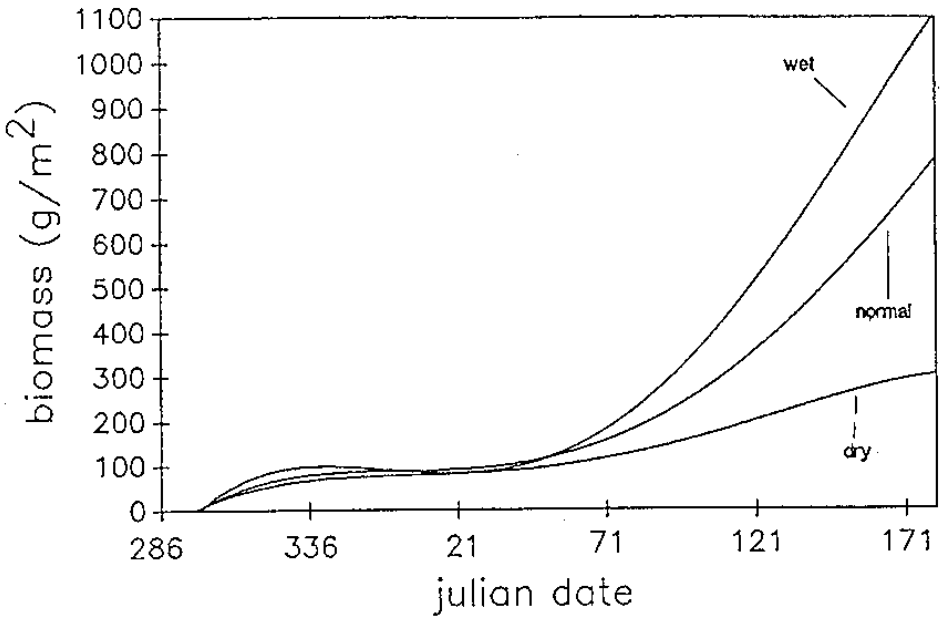

Fig. 5. Simulated mean biomass accumulation during the growing season for wet, normal and dry years for winter wheat at Ashland, Kansas.

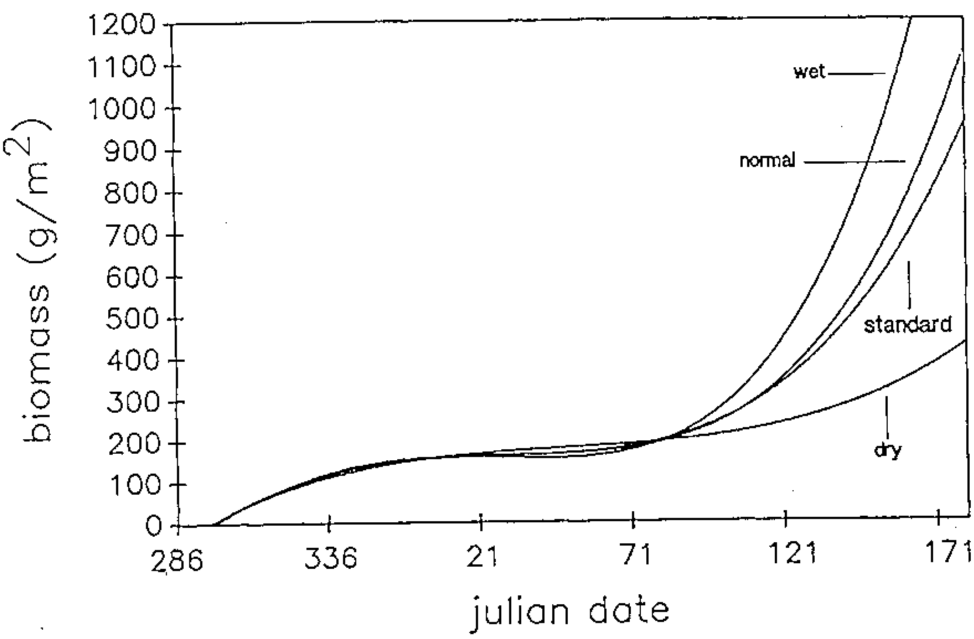

Fig. 6. Simulated biomass accumulation during the growing season for the standard year and for wet, normal and dry conditions after the end of growth stage I. (julian date 103).

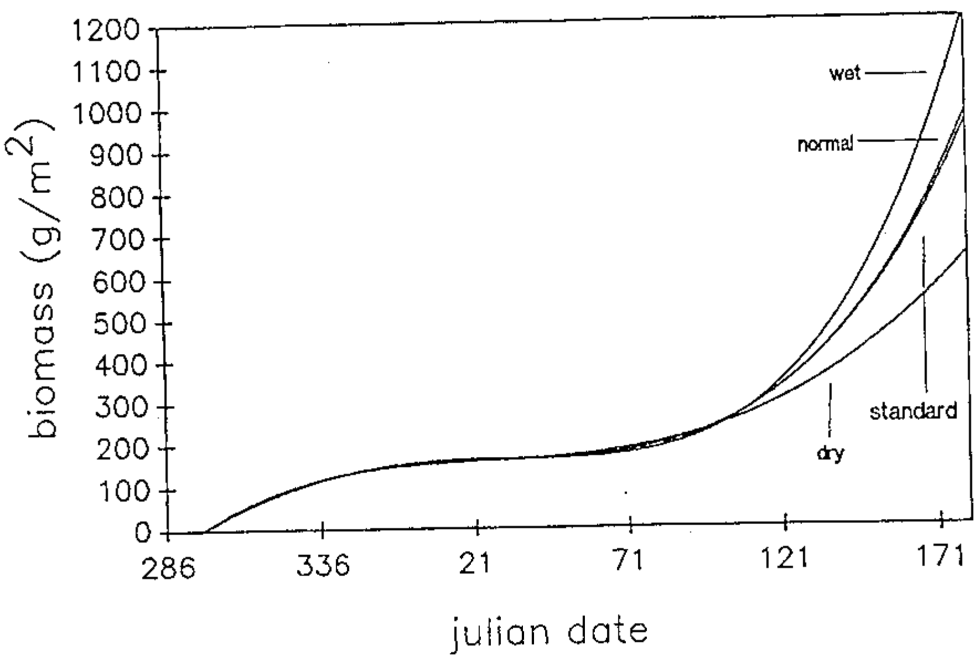

Fig. 7. Simulated biomass accumulation during the growing season for the standard year and for wet, normal and dry conditions after the end of growth stage II. (julian day 126).

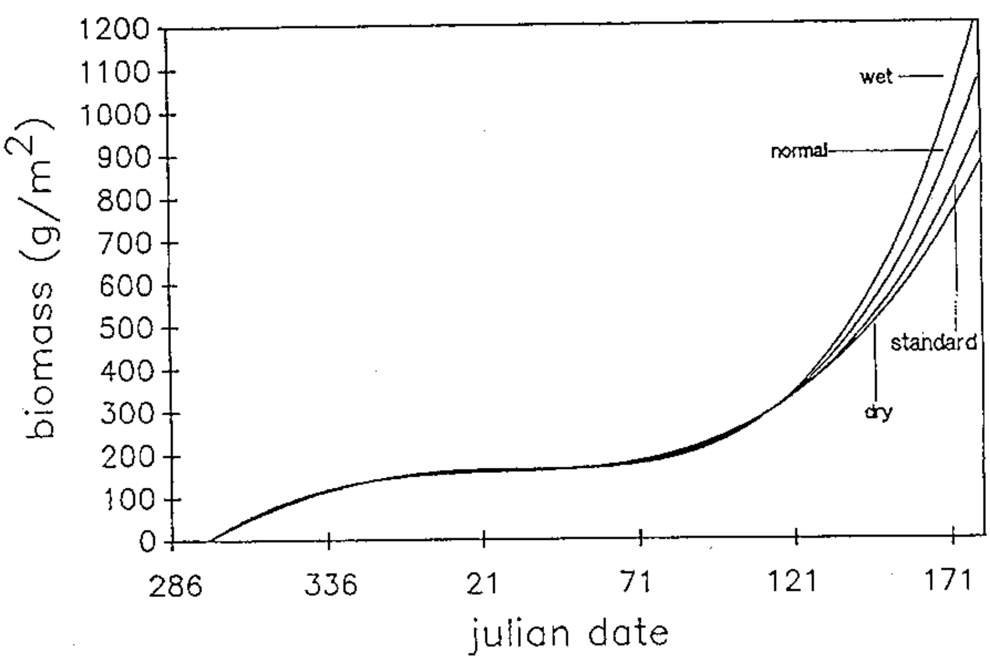

Fig. 8. Simulated biomass accumulation during the growing season for the standard year and for wet, normal and dry conditions after the end of growth stage III. (julian day 137).

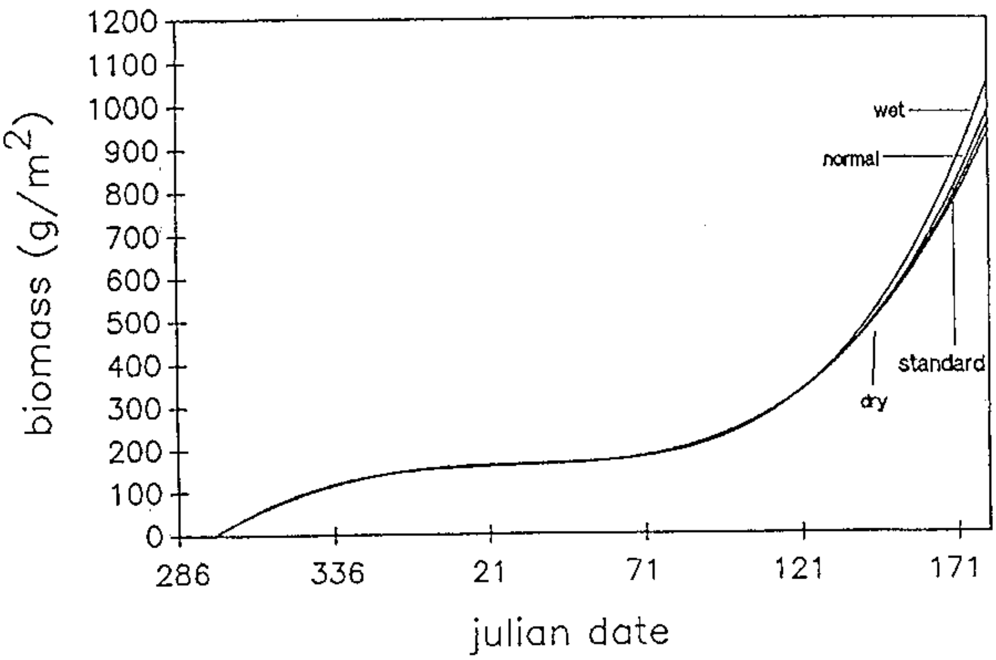

Fig. 9. Simulated biomass accumulation during the growing season for the standard year and wet, normal and dry conditions after the end of growth stage IV. (julian day 146).

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WEATHER SIMULATION AND ITS APPLICATION TO CROP YIELD FORECASTING

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ABSTRACT

Methods of weather and crop yield forecasting are reviewed. Uncertainty in weather forecasting produccs uncertainty in crop yield forecasting. A dynamic and probabilistic approach which integrates weather and crop simulation models is suggested for forecasting. In the paper, an example of forecasting wheat yields for Ashland, Kansas is shown. Results demonstrated that (1) different weather scenarios can be evaluated along with normal weather patterns with prescribed probabilities of the likelihood of the occurrence of the events, (2) the use of dynamic models can provide useful information about the growth and development of the crop in addition to the yields, (3) progressive forecasting can be made as real weather data accumulates over the growing season and the final simulation result will necessarily converge to the observation.

INTRODUCTION

Agricultural development and systems are primarily determined by long-term climate. When developing a responsive, productive and efficient farming system, an understanding of the climatic condition in an environment is essential along with considerations of selecting suitable crops and rotation systems and approaches for cultural and pest management practices. In contrast, shortterm weather conditions in a growing season determine the actual output level of an agricultural system, and the production level fluctuates according to the weather variation from one year to another. In this context, human history can be seen as man's struggle to maximize agricultural productivity in the face of uncertain weather conditions. Over the years, mankind has successfully developed sophisticated irrigation systems, various resistant cultivars, and other chemical and mechanical technologies to improve agricultural productivity particularly in the so-called "good" years. But when the weather is "bad", there are detrimental effects on agriculture. This was true 4000 years ago and is true today in the 20th century.

A case in point is the corn yields in the United States and grain production in the world. U.S. corn yield had five sharply reduced harvests since 1950 (Figure 1). Except in 1970 when the yield reduction was caused by an outbreak of corn blight, all other reductions were related to poor weather conditions. Three of the pronounced reductions occurred in the 1980's and were all due to drought. Compared with the preceding years, the yields were reduced by 17%, 28%, and 34%, respectively, for 1980, 1983, and 1988 (Brown and Young, 1988). Overall grain production in the U.S. was down by 29% in 1988, marking perhaps the first time in recent history that the U.S. grain harvest fell below domestic consumption. Since the United States is the largest grain exporting country, the impact of this reduction is felt in all food-importing countries worldwide. Indeed data of world grain production and consumption showed deficits of food supply in these years (Figure 2). A global indicator of food security is "carryover stocks" of grain or the amount in the bin when the new harvest begins. This amount can be converted to consumption equivalent days which normally are expected to fall between 60 to 90 days. As total grain production has declined, so too have carryover stocks. In 1988, world food consumption is estimated to exceed production by 152 million metric tons, and the carryover stocks are expected to fall to roughly 54 consumption equivalent days (Figure 2). This is the lowest number of days since 1960 and is less than the 57-day supply of 1972 which doubled world grain prices. It would obviously be advantageous to all nations if levels of agricultural production can be predicted within a reasonable time period, and sensible policies are developed to case the problems.

In order to predict the impact of weather on crop production, we must first be able to predict the weather and to understand the relationship between weather variables and crop growth and yield characteristics.

Factors affecting long-term climate. Historical records suggest that subtle variations in the sun's energy output can have decidedly unsubtle effects on the earth's climate. Solar variability presumably reflects turmoil in the interior of the sun. Sunspots, which are essentially magnetic storms caused by inner turbulence, are found to occur in 11-year cycles (Waldrop, 1989). The enhanced sunspot activity results in global warming on earth.

Another factor affecting long-term climate on earth is El Niño, an atmospheric and oceanic interaction phenomenon that occurs every three to five years in the eastern Pacific Ocean. El Niño is known to bring heavy winter rains to Peruvian deserts and warm weather to the U.S. A lesser known sibling but reverse phenomenon is called La Niña. As opposed to El Niño, La Niña is credited with bringing in cold temperatures to the eastern Pacific in winter, drier weather in Peru and Chile, and flooding on the Indian subcontinent. The two phenomena make up the extremes of a giant meteorological system called the Southern Oscillation which functions as a giant heat pump distributing energy from the equator to the higher latitudes through storms brewed over the warm western Pacific (Linden, 1988; Rusting, 1988). Handler and Handler (1983) found a correlation between corn yields in the United States and the El Niño events. They suggested that in years in which an El Niño event causes surface temperatures in the tropical Pacific to become higher than normal, there is a higher probability of an above-average corn yield in the United States.

Marine geologists generally believe that the length of inter-glacial periods is on average 10,000 years ±1,000 years. Bryson (1975) argued that we are virtually on the eve of entering a glacial period. He showed that there is a pronounced climatic change in the Aretic as it becomes cloudier and has more snowfall in winter. Since the difference in temperature between the Arctic and the rest of the world drives the atmosphere and determines the eirculation pattern on earth, the change in the Arctic will affect the rainfall pattern in the Northern Hemisphere. Bryson predicted that the expansion of the circumpolar vortex would bring damp weather to western Europe, reduce summer rainfall in the Great Plains of the United States, and disturb the monsoon system in tropical and subtropical regions.

Unfortunately, many of these long-term climatic phenomcna can neither be explained nor predicted with a high degree of accuracy. Many of the fundamental features or underlying physical mechanisms of these events have remained a mystery, e.g., why should the sunspots erupt periodically? Why is it an 11-year instead of a 5-year or even 20-year sunspot cycle? What is the mechanism that links El Niño and La Niña?

Recently, global warming due to the increase in greenhouse gases has gained considerable attention scientifically and politically. Newly collected and accumulated data indicate that the atmospheric CO_2 concentration has increased by about 25% since 1850 because of fossil fuel and coal combustion. In addition, an increase in methane (produced by everything from cattle to rice paddies) and chlorofluorocarbons (well-known for causing ozone depletion) among other trace nitrogen oxides could upset the earth's radiative balance and significantly enhance the warming of the earth (Kerr, 1986; Flavin, 1988). The effect of these gases on present and future temperature and rainfall is uncertain. However, results from the most recent global clmatic model analyses suggest that global average surface temperatures will increase by 2° to 6°C during the next century. Although these models are some of the most effective tools for analyzing global climate, they suffer from lack of comprehensive feedback systems which would include snow coverage, cloud types, and oceanic and biological reactions to the increased gases. Unless all countries jointly design an effective strategy to stop the emission of these gases into the atmosphere, the increased gases will have a major impact on weather, water resources, sea level, forests, biological diversity, air quality, urban infrastructure, human health, and electricity demand (Schncider, 1989).

WEATHER AND CROP YIELD FORECASTING METHODS

Weather forecasting methods. In the hopes of understanding and forecasting atmospheric variability on time scales of weeks or months, atmospheric teleconnection, statistically significant temporal correlations between meteorological parameters at widely separated points, have been studied for the Northern Hemisphere (Namias, 1981; Wallace and Gutzler, 1981) and for the Southern Hemisphere (Mo and White, 1985; Trenberth and Mo, 1985). Harry van Loon and Roland Madden of the National Center for Atmospheric Research in Boulder, Colorado found evidence that Darwin, on the north coast of Australia, has a teleconnection with Duluth, Minnesota, among other places. For example, when average winter pressure is abnormally high at Darwin, winter temperatures in the southern United States tend to be below normal, and temperatures in California, the north-central United States (including Duluth) and western Canada tend to be higher than normal. Areas having consistent correlation with Darwin's pressure are also found in the eastern north Atlantic over the Caspian Sea, in India, Japan, and part of Siberia. Thus, in spite of the great distances and the general west-to-east movement of weather in the middle latitudes, a network of teleconnections links the equatorial Southern Oscillation with weather far to the north (Kerr, 1982). Tim Barnett of Scripps Institute of Oceanography found that Pacific sea surface temperature can be used to predict U.S. air temperature a season ahead with variable accuracy depending on season and location.

Although aesthetically enticing, the above statistical approach based on the concept of stimulus-response may not be appropriate for extended-range forecasting. The basic problem is the inability of meteorologists to ascertain unambiguously the dynamic mechanisms that control the evolution of the variable meteorological phenomena. Without this knowledge, no scientific gorunds exist on which to base an extended-range forecast or to judge whether the mathematical formulations of numerical models are complete enough to accurately represent low-frequency meteorological behavior (Reinhold, 1987).

In practice, long-range (monthly or seasonal) forecasts have been based on empirical and probabilistic approaches. The primary format for the U.S. National Weather Service's long-range precipitation will exceed or fall short of its climatological expectation. The forecasting actually involves three steps. First, the forecaster tries to forecast the mean tropospheric flow pattern for the period in question at an elevation of about 3 km (10,000 ft.) expressed as a departure from the long-term climate mean for that period. The second step is to infer from the anomalies in this flow pattern the patterns of temperature and precipitation anomaly. The final step is the assignment of probability (Epstein, 1988).

Most of the advances made in recent years in weather forecasting are in the areas of shortterm (less than 3 days) and medium-range (less than 10 days) predictions. Tribbia and Anthes (1987) presented a review of the scientific principles and computational methods used for weather predictions. They point out that current numerical weather models consider many physical processes: the latent heating of condensation in clouds; absorption and emission of radiation by the radiatively active constituents CO_2, H_2O, and O_3; absorption and scattering of radiation by clouds and aerosis; and addition of heat, moisture and frictional forces at the earth's surface. In addition, these models require an analysis of huge numbers of diverse data from land-surface stations, ships, ocean buoys, satellites, aircraft, and balloons to provide initial values for the forecasting variables in the model.

In 1963, Edward Lorenz's findings shattered the hope that improved numerical models which relate important meteorological variables and incorporate complex physical systems would one day be able to accurately predict weather. Lorenz concluded that weather is inherently unpredictable. He demonstrated that the lack of predictability arises from a sensitivity to initial conditions, meaning the solution of the numerical models would change completely if the starting point were altered by even a tiny amount (Pool, 1989). This type of behavior is now called "chaotic".

Nevertheless, because even chaotic systems obey mathematical logic, there is regularity beneath the disorder. The implications of a chaotic system are two-fold. First, science may never understand certain phenomena. Second, much of the complicated, seemingly random behavior in the world may actually be simple in origin; it may be much easier to analyze this complexity than was previously believed. In fact, several meteorological modelers have used ideas from chaotic theory to mimic and simulate weather behavior (Vallos, 1986; Tsonis and Elsner, 1989).

Methods for yield prediction. For agricultural scientists, the ultimate purpose of weather prediction is to predict yields. Accurate yield prediction is a considerably more difficult task than accurate weather prediction since it requires additional knowledge and quantified functional relationships between weather variables and crop characteristics. The simplest expression of weather-yield relationship is:

biomass = (water-use efficiency) x (transpiration).

Both water-use efficiency (WUE) and transpiration (T) are genetic and weather dependent variables. Various models were developed from this basic formula to explicity define WUE and T and therefore provide useful tools to estimate biomass yield for a given crop and set of weather conditions (Noy-Meir and Harpza, 1977; Uchijima and Seino, 1985).

However, most papers in the literature which examine the weather-crop yield relationship used an empirical multiple regression approach (e.g. Kogan, 1985; Garcia et al., 1987; Thompson, 1988). Some regression models involved an integration of several sub-regression models, each of which was constructed for a phenological stage of the crop development (Feyerherm and Paulsen, 1981, 1986) or for a defined growth period (Michaels, 1978). These models were inductive models based on observations without a need to define the cause-effect relationships among the variables included in the model. Due to the lack of biological and physical explanations in these models, they were often criticized for providing no scientific insights about the phenomena under investigation and were limited in scope of interpretation and ability for extrapolation.

As the understanding of plant life and the availability of powerful microcomputers has increased, the simulation approach based on explanatory models to analyze agricultural systems and to predict crop production has also gained popularity. These models include considerations of physiological processes such as photosynthesis, respiration, transpiration, partition of assimilation, and phenological development (de Wit, 1965; de Wit et al., 1978; Loomis et al., 1979). Penning de Vries and van Laar (1982) documented some advancements made in plant simulation studies by scientists in the Netherlands. Whisler et al. (1986) presented a review and a summary of crop simulation models developed for agronomic applications. Examples of the application of crop simulation models for yield forecasting can be found in Baier (1973), Arkin et al. (1980) and more recently in Algozin et al. (1988).

In the following section, we will describe an integrated simulation approach for crop yield prediction.

AN INTEGRATED SIMULATION APPROACH

The integrated simulation approach involves the following steps:

1. Select a crop growth and development model.
2. Select a weather data generator which is capable of generating representative weather patterns and the yearly variations for a location.
3. Generate 100 years of weather data with the weather generator and 100 years yield data with the crop model.
4. From the yield and weather distributions, evaluate the likelihood of extreme events such as dry and wet years and their yields.
5. Select dry and wet year events according to a prescribed probability.
6. The extreme years (with a given probability level) and the mean year events provide three possible scenarios for forecasting applications.

This approach is illustrated by the following wheat yield forecasting example.

Crop model. While many models have been developed for rice and wheat, we will use the CERES-Wheat model (Ritchie and Otter, 1985) which has been extensively validated for winter and spring wheat production in the Great Plains of the United States (Larsen, 1985). This model includes routines which analyze: phasic development or duration of growth stages as influenced by plant genetics and weather variables; biomass production and partitioning; and soil water and nutrient uptake. The CERES-Wheat model requires the following inputs: daily solar radiation, minimum and maximum temperature, and precipitation; soil drainage, runoff, evaporation, and radiation reflection coefficients; soil water and nitrogen profiles; latitude of the production location; genetic coefficients or thermal time required for developmental stages; management information such as plant density, planting date, irrigation, and N fertilization.

Weather model. Weather simulation models can be used in connection with crop or disease models to evaluate the impact of weather on crop production. But most available weather models require long-term historical daily weather data to estimate model parameters. This requirement severely restricts the applicability of the models. Geng et al. (1986, 1987, 1988) have developed a computer simulation program, SIMMETEO, which can generate daily weather variables such as rainfall, maximum and minimum temperature, total solar radiation, average humidity and average wind speed based on long-term monthly averages of these variables. This program has been tested in distinctly different locations including Los Banos, the Philippines, Wageningen, the Netherlands, and several locations in the United States. Table 1 shows some simulation results obtained from 14 locations in 7 states of the Great Plains in the United States.

Data selection. For the purpose of illustration, we will focus on only one location, Ashland, Kansas. Monthly averages of all relevant meteorological variables were read in by SIMMETEO and 100 years weather data were generated. Figure 3b represents the annual rainfall distribution of the simulated 100 years data. Based on the distribution of normal rainfall, one can determine the upper 2.5% and the lower 2.5% amount of annual rainfall. The cut-off points of these amounts of rainfall provide sets of conditions for wet and dry years. These conditions are then used to generate weather data for 100 wet and 100 dry years. The distributions of the annual rainfall for the wet and dry years are shown in Figures 3a and 3c, respectively. The amount of rainfall during a growing season for each of these years was calculated and the corresponding distributions of wet, normal and dry years are shown in Figure 4. These simulated weather data will then be used as inputs for the wheat model to generate biomass yield curves.

The input data for the CERES-Wheat model were obtained from the Decision Support System for Agrotechnology Transfer (DSSAT) of the International Benchmark Sites Network for Agrotechnology Transfer (IBSNAT Technical Report No. 5, 1986). This information included plant genetic coefficients and soil type information such as soil profile properties, nitrogen balance parameters and initial conditions.

SIMULATION RESULTS AND DISCUSSION

The CERES-Wheat model was run to generate 100 years of data under each of the wet, normal and dry conditions to ascertain the biomass and yield distributions. The average daily biomass accumulation during the growing season for the three conditions is shown in Figure 5. The biomass accumulation for the three conditions is very close until about julian day 40. After that day the wet and normal weather show more rapid growth rates than the dry weather. The biomass (kg/ha) at maturity for wet, normal and dry conditions is 9140, 6488 and 3115, respectively. The wet year biomass at maturity was 41% higher than the normal year while the dry year was only 48% of the normal year biomass. The mean harvest index for wet, normal and dry years was 0.30, 0.26, 0.21, respectively, giving mean grain yields of 2742, 1687 and 656 kg/ha, respectively.

The growing season was divided into 5 stages based on the CERES-Wheat model: I. seedling emergence to appearance of the terminal spikelet (including a dormancy period for winter wheat); II. appearance of the terminal spikelet to the end of vegetative growth; III. the end of vegetative growth to the end of ear growth; IV. the end of ear growth to the beginning of grain filling; and V. grain filling to maturity.

A crop year with average rainfall and grain yield for the 100 years of normal weather conditions was chosen as the standard year against which to forecast grain yield. Typical wet, normal and dry years were selected to predict grain yield in the standard year. An updating technique was used in which four grain yield forecasts are made based on available weather information as the growing season progresses: (1) First yield forecast – observed weather is available only through the end of growth stage I (julian day 103). The three possible weather conditions (wet, normal and dry) after that day are simulated and the predicted biomass and grain yields are obtained to form the first yield forecast. (2) The first weather update and second yield forecast – observed weather is added through the end of growth stage II (julian day 126). Again, three possible weather conditions (wet, normal and dry) after that day are simulated. (3) The second weather update and third yield forecast – observed weather is utilized through the end of growth stage III (julian day 137). The three possible weather conditions after that day are simulated. (4) The third weather update and fourth yield forecast – observed weather is utilized through the end of growth stage IV (julian day 146). The three weather conditions after that day are simulated. Planting date was julian day 280 and maturity date for all the simulations was between julian day 168 and 171 of the following year.

The first forecast utilized observed weather through the end of growth stage I (julian day 103) and simulated weather thereafter. Figure 6 shows the results of those simulations. The three rainfall conditions result in very different biomass and yield predictions. The predicted accumulated biomass (kg/ha) at maturity for wet, normal and dry conditions after day 103 was 11,110, 7166 and 3410 and the predicted grain yield (kg/ha) was 3736, 2263, and 797, respectively. The standard year had an accumulated biomass at maturity of 6510 kg/ha and a grain yield of 1605 kg/ha. The standard year grain yield and the normal year grain yield forecast differed by 658 kg/ha. Because this is a long-term forecast made 68 days before maturity and before most of the rapid vegetative growth has taken place, the predicted grain yields are subject to error. However, Figure 6 shows the full range of expected yields given the weather conditions during the first stage of plant growth.

The first weather update (second grain forecast) utilized observed weather through the end of growth stage II (julian day 126). Predicted biomass (kg/ha) at maturity for wet, normal and dry condition after day 126 was 8350, 6670 and 4880 (Figure 7) and the predicted yield (kg/ha) was 3249, 1748 and 897, respectively. The normal year grain yield forecast differed from the standard year grain yield by 143 kg/ha. For this second forecast, still a long-term forecast 45 days before maturity, the range between the highest grain yield (under wet conditions) and the lowest yield (under dry conditions) was 2352 kg/ha.

The second weather update (third grain forecast) utilized observed weather through the end of growth stage III (julian day 137). The predicted biomass at maturity (kg/ha) for wet, normal and dry conditions after day 137 was 8290, 7118 and 5870 (Figure 8) and the predicted grain yield (kg/ha) was 2934, 2128 and 996, respectively. The range between the high and low predicted yields was 1938 kg/ha. The normal year prediction differs from the standard year by 523 kg/ha, a larger difference at this forecast that the previous one because of the rainfall added from the standard year to the normal year in growth stage III. The weather used for prediction combined with the standard weather up to julian day 137 resulted in more total growing season rain (287mm) than during the previous update and forecast (268mm) which used observed weather only up to julian day 126 and predicted weather thereafter. This illustrates the importance of considering both the amount and distribution of rainfall during the growing season.

The third weather update (fourth grain forecast) utilized observed weather through the end of growth stage IV. (julian day 146). The predicted biomass (kg/ha) at maturity for wet, normal and dry conditions after day 146 was 6990, 6490 and 6320 (Figure 9) and the predicted grain yield (kg/ha) was 1929, 1566 and 1443, respectively. The forecasted grain yield for normal weather conditions and the standard grain yield differed by only 39 kg/ha. The range between the high and low grain yields was 468 kg/ha. The three grain yield predictions (wet, normal and dry) were all close to the observed yield of 1605 kg/ha.

These results indicate that a reliable grain yield prediction can be made at the beginning of grain filling (growth stage IV, 23 days before maturity) and possibly at the end of vegetative growth (growth stage III, 34 days before maturity). The forecasts at the end of growth stages I and II (68 and 45 days, respectively, before maturity) give the range in which final yields can be expected to fall.

The USDA makes monthly, seasonal, and annual forecasts of crop yields for the United States and the rest of the world. The USDA's method of projections is considered a model and is followed by other international agencies including the United Nations. This method, based mainly on regression models, has been criticized by climatologists who argue that its reliance on past yields and normal weather is an erroneous guide to the future (Shapley, 1976). Part of the criticism of the USDA's approach is alleviated by the method presented in this paper. First, different weather cenarios can be evaluated along with normal weather conditions with prescribed probabilities of the likelihood of the occurrence of the events. Second, the use of a dynamic crop model will provide not only prediction of final yields but also information about the growth and development of the crop. Third, the dynamic and probabilistic approach provides a tool which allows for a progressive and self-correcting forecasting process. In other words, as more information becomes available during later growing seasons, different forecasting scenarios will converge to a common prediction with increasing probability of being correct.

The simulation and forecasting methods we have discussed above do not include those factors that may affect long-term weather changes. The difficulty of including those considerations is that their effects are usually smaller than the random fluctuation existing between the years. This point is also illustrated in Figure 3 and 4 where there is a great deal of overlapping between the distributions of wet, normal, and dry years. In other words, even though the means among the populations are different, it would be difficult to determine which population (wet, normal, or dry) a given year was taken from. The problem of how the future trend of weather changes can be effectively included in the simulation presents a challenge for future research.

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