Partial Adoption of Divisible Technologies in Agriculture

Philip I. Szmedra, Michael E. Wetzstein, and Ronald W. McClendon

Abstract *We have developed a dynamic theoretical model to investigate technology complements where the degree of adoption is a function of producers' prior technology levels. Based on this model, we used an empirical application to assess the adoption of integrated pest management (IPM) with and without irrigation. Results indicate that the degree of new technology adoption may depend on the extent of the risk. For example, strongly risk-averse producers who use dryland technology may only partially adopt IPM. And producers who irrigate to significantly decrease variation in yield and returns may also only partially adopt IPM.*

Keywords. *Pest management, irrigation, simulation, soybeans, technology adoption*

Conventional theories describing technology adoption in agriculture have addressed constraints to adoption associated with profitability, riskiness, and divisibility. These constraints generally deal with farm tenure arrangements, aversion to risk, imperfect information markets, inadequate farm size, and lack of credit (*8*).[1] Availability of technologies has been investigated for inappropriate infrastructure, chaotic supply of complementary inputs, and absence of equipment to relieve labor shortages (*3*). Removing these constraints, however, has generally not resulted in immediate adoption, which focuses attention on complexity and how it influences new technology adoption.

Theoretical research and empirical research attempt to isolate the characteristics of separate technologies as the key determinants of the adoption decision (*5*). Byerlee and de Polanco provide evidence that farmers adopt in a sequential manner, in some instances adopting a complete package of new technologies, but more likely practice partial adoption by accepting only a portion of a technology (*3*). Farmer decisions regarding new technology adoption probably depend on the number and complexity of existing production technologies and the way in which a new technique would complement the existing technology mix. Our article considers this notion.

The article investigates farmer decisions regarding technology adoption when an existing set of prior technologies is considered. A theoretical model designed to investigate technology complements is developed in a stochastic setting, where the degree of adoption is a function of producers' prior technology levels. An application reveals varying levels of integrated pest management (IPM) adoption for soybean farmers with and without prior irrigation technology.

Analytical Framework

Development of a theoretical model that incorporates various levels of a prior technology, partial or total adoption of new technologies, producers' production and profit functions, and the stochastic nature of returns may give insight into the technology adoption process. Building on the groundwork of Antle, and Caswell and Zilberman, we let $q_{t+1} = f[q_t(e_t)]$ represent a production transformation from time t to t+1 in an annual production process (t = 1, ..., T). Where q_t denotes the state of the output in time t, e_t is a decision variable and denotes the degree of adoption of a new technology package, $q_t(e_t)$, is a function representing the effect of e_t on q_t, and f( ) is a function representing the change in the state of output from time t to t+1 given q_t and e_t. The state of output may define the conditions of the soybean crop, including vegetative growth, blooms, and fruit set. Defining a_t as the amount of the new technology available or purchased, variable e_t represents partial adoption of this new technology. In terms of pest information, e_t denotes the subset of the information technology package purchased by the farmer in time period t which is actually incorporated into the production process.

Based on farmers' level of technical expertise, the type of production technologies currently being used, and the complexity arising from attempting to successfully integrate current methods, farmers may incorporate only a portion of a new technology into their production process. The level of farmers' prior technology, α, influences both $e^*_t(\alpha)$ and $a^*_t(\alpha)$, where $e^*_t(\alpha)$ and $a^*_t(\alpha)$ denote the effective level of partial adoption and the optimal amount of the new technology purchased, respectively. The ratio of partial adoption to purchased technology is also determined by α, denoted as $h_t(\alpha)$, and is defined by the identity $h_t(\alpha) \equiv e_t(\alpha)/a_t(\alpha)$. This identity provides a link between the level of partial adoption and the level of a purchased technology.

As noted by Byerlee and de Polanco, interactions among technologies will affect adoption patterns. If a new technology package tends to complement prior technologies, then $h_t' > 0$, $h_t'' < 0$, where $h_t' = dh/d\alpha$ and $h_t'' = d^2h/d\alpha^2$. However, if a substitution relation

Szmedra is an agricultural economist with the Resources and Technology Division, ERS. Wetzstein is a professor, Department of Agricultural Economics, Univ. of Georgia, Athens, and McClendon is an associate professor, Department of Agricultural Engineering, University of Georgia, Athens.

[1] Italicized numbers in parentheses cite sources listed in the References section at the end of the article.

exists, then $h_t' < 0, h_t'' = 0$ The derivative relations indicate the effectiveness with which the new technology is integrated into the production scheme A complement relationship between prior and new technologies indicates that an increase in prior technology will increase degree of adoption of the new technology at an increasing rate, whereas a substitute relationship indicates that an increase in prior technology will increase degree of adoption of the new technology at a decreasing rate

Expected net return in the initial time period, $E(\pi_1)$, resulting from the adoption of a new technology, can be specified as

$$E[\pi_1(q_1, e_1, \quad , e_T)] = \sum_{t=1}^{T} E[I_t(q_t, e_t)],$$

where E is the expectations operator and $I_t(\ )$ denotes the distribution of returns at time period t The functional form of $I_t(\ )$ is

$$I_t(q_t, e_t) = p_t q_t - w_t a_t,$$

where p_t is output price associated with the marketable portion of q_t, and $w_t a_t$ denotes the cost of the technology package in period t. If all of the output is harvested at terminal time, T, then $I_t \geq 0$ for t = 1, , T–1 and $I_t > 0$ at T The solution to this problem may be obtained with dynamic programming (*13*) Let $p_t^*(q_t)$ denote the optimal performance function which is the optimal value of q_t for problems starting at state q_t at time t By the optimality principle,

$$\pi_t^*(q_t) = \max_{a_t} \{E(I_t) + \pi p^*_{+1}[f(q_t, e_t)]\}$$

The first-order condition for maximization of $\pi_t^*(q_t)$ is

$$\partial \pi_t^*(q_t)/\partial a_t = \partial E(I_t)/\partial a_t + \partial p^*_{+1}/\partial a_t = 0 \qquad (1)$$

Risk preference may be incorporated into the objective function by replacing expected returns in time t with farmer preference ordering, $U(I_t)$, assuming the eight postulates outlined by Just and Pope (*12*) Given an analytic function, a Taylor series expansion about the expected value of I_t, $E(I_t)$, is

$$U(I_t) = \sum_{k=0}^{\infty} \{E[I_t - E(I_t)]^k/k!\} U^{(k)},$$

where $U^{(k)}$ denotes the k^{th} derivative of U Thus, the utility function of a risky prospect I_t is assumed to be equal to the utility function evaluated at the first moment of I_t plus the products of the higher moments of I_t, the corresponding derivative of the utility function, and the inverse factorial Letting M_k denote the k^{th} moment of I_t, the first-order maximization of U = $U(M_0, M_1, M_2, \quad , M_\infty)$ yields

$$\partial U(I_t)/\partial_{at} = \sum_{k=0}^{\infty} (\partial U/\partial M_k)(\partial M_k/\partial a_t) = 0$$

Note that

$$\partial M_0/\partial a_t = \partial E(I_t)/\partial a_t = p_t q_t' h_t - w_t,$$

given $q_t(e_t)$, $e_t = h_t a_t$, and $q_t' = \partial q_t/\partial e_t$

Thus, this follows

$$\partial U(I_t)/\partial a_t = [\partial U/\partial E(I_t)](p_t q_t' h_t - w_t)$$

$$+ \sum_{k=1}^{\infty} (\partial U/\partial M_k)(\partial M_k/\partial a_t) = 0 \qquad (2)$$

Incorporating risk preference into equation 1 given equation 2 yields

$$\partial \pi_t^*(q_t)/\partial a_t = \partial U(I_t)/\partial a_t + \partial p^*_{+1}/\partial a_t = 0$$

Rearranging terms yields

$$w_t = p_t q_t' h_t + \sum_{k=1}^{\infty} \{(\partial U/\partial M_k)/[\partial U/\partial E(I_t)]\} (\partial M_k/\partial a_t)$$

$$+ (\partial p^*_{+1}/\partial a_t)/[\partial U/\partial E(I_t)] \qquad (3)$$

The optimal value of available or purchased technologies, a_t, occurs when the marginal cost of a_t equals the value of expected marginal product times the adoption ratio plus the summation of the rate of utility substitution between E(I) and M_k moments plus the future marginal increment to the objective functional weighted by producer's marginal preferences Thus, both risk preference and dynamic production influence the optimal level of available technology

The relative importance of modeling risk preference versus dynamics is open to empirical investigation However, of interest in this study is the influence of a prior technology and risk aversion on adoption of new technologies. First, consider a producer's optimal adoption level of a technology given a prior technology by isolating prior technology effects from risk aversion Following Caswell and Zilberman's assumption of a static production relation and without loss of generality, a producer's optimal amount of a new technology package is determined by total differentiation of equation 1 and by analyzing the comparative statics results This gives

$$pq''(ha' + ah')h + pq'h' = 0,$$

where $q'' = \partial^2 q/\partial e^2$ and $a' = da/da$

Rearranging terms yields

$$a' = -a\phi/\alpha + a\phi/\alpha\epsilon, \qquad (4)$$

where $u = h'a/h$ denotes the elasticity of partial technology adoption, and $e = -q''e/q'$ denotes the elasticity of marginal product of partial technology adoption The total effect of a change in prior technology, a, on purchases of the new technology, a, is a' This total effect may be decomposed into the substitution and output effects, the first and second terms on the right-hand side of equation 4 If ϵ is zero, the degree of adoption, e, does not influence the marginal product of adoption Thus, the output effect associated with the influence of a change in α on a is zero, and only the substitution effect remains If ϵ equals one, however, the output effect just offsets the substitution effect and the total effect, a', is zero As indicated in equation 4, the level of new technology adoption, e, influences the degree to which prior technology affects new technology purchases When a new technology package tends to complement a prior technology ($h' > 0$), then

$$a' \lesseqgtr 0 \text{ if } \epsilon \lesseqgtr 1$$

A relatively strong decrease in marginal product of partial adoption is associated with $\epsilon > 1$ given an increase in e, while $0 < \epsilon < 1$ corresponds to a relatively small change in marginal product Thus, for $\epsilon > 1$ the decline in marginal product offsets the increase in h resulting in $a' < 0$ Alternatively, a new technology package, a, that is a substitute for prior technology ($h' < 0$), results in

$$a' \lesseqgtr 0 \text{ if } \epsilon \lesseqgtr 1$$

When $\epsilon > 1$ the increase in marginal product offsets the decline in h resulting in $a' > 0$ [2]

A consideration of risk or dynamic properties may either mitigate or augment the response of a to a change in α Analysis using comparative statics methods when risk and dynamics are incorporated usually results in intractable outcomes However, assuming risk-averse producer behavior, it may be hypothesized that if a is a risk-reducing (-increasing) technology, the greater the effect of a on the second and subsequent moments of π, given a change in α, the higher (lower) is the adoption rate of a In a dynamic risk-neutral model, if an increase in a reduces the π moments' magnitudes, a higher adoption rate of a may be hypothesized Thus, the risk and dynamic processes may work in tandem and are not necessarily mutually exclusive

An implication of this analysis is that a heterogeneous set of prior technologies cannot be ignored when the adoption of new technologies is being investigated

[2]Note that e' is proportional to h'

Feder and others noted that when prior technologies are constantly being modified with the addition of new technologies, equilibrium may never be attained (*8*) This is particularly true when risk preferences and dynamic processes are considered

Application

Much of the empirical work on technology adoption has lacked a theoretical and biophysical basis on which to specify relations and interdependencies Endogenous variables are often employed as explanatory variables without regard for the simultaneous equation bias that may result (*8*) Dynamic programming provides an indication of which policies should be investigated further Finding an optimal policy using dynamic programming, however, becomes intractable as the complexity of a process increases Simulation modeling is an alternative method Useful for analysis is a simulation model comprised of a system of differential equations detailing crop growth, including soil, water, insect growth and damage, and economic components that include endogeneous constraints such as producers' risk aversion A combination of risk and dynamics is a standard justification for use of simulation models (*11*)

The Soybean Integrated Crop Management Model

We used the Soybean Integrated Crop Management Model (SICM) to demonstrate the technology adoption model developed above (*23*) SICM allows a comprehensive development of insect and crop interaction The SICM model incorporates soil, water, insect, and economic components in detailing crop growth The primary component of the SICM model is SOYGRO, a soybean growth and yield routine Physiological processes of photosynthesis, respiration, tissue synthesis, nitrogen remobilization, and senescence in the model depend on weather, as well as soil and crop conditions These processes are linked mathematically by a series of differential equations that depend on the phenological phase of crop development The mathematical structure of the soybean crop model describes processes or parameters that depend on growth phase, weather, and the state of the crop to update the evolution of the crop cycle

The model includes three insect routines which represent the principal sources of diminished yield in soybeans due to insect damage in the Southeastern United States The insects are the velvetbean caterpillar (VBC), *Anticarsia gemmatalis* (Hubner), the corn earworm (CEW), *Heliothis zea* (Boddie), and the southern green stinkbug (SGSB), *Nezara viridula* (L) The SICM model divides VBC developmental stages into six distinct periods which are both temperature- and insect-related individual dependents The length of time required for a VBC larva to develop from one stage to the next varies with temperature and also varies among VBC in different development stages raised at identical temperatures. Insects move through age categories within a given growth stage until they have accumulated a sufficient number of physiological days to advance to the next development stage (*14*, *23*). One physiological day is defined as the proportion of development completed in 1 day at 26.7°C.

The CEW population model developed by Stinner and others uses a variation in development time for a given temperature to estimate the change in generations (*20*). The model indicates the value of variables daily and calculates stage populations, damage to seeds, pods, and foliage for each developmental stage, and mortality from all sources. The third insect model describing SGSB is based on the work of Rudd and incorporates emergence functions to develop probability distributions for SGSB progression through development stages (*19*).

The pesticide tactics component simulates the effect of specific insecticides on individual development stages of each of the three insects including residual effectiveness over time. The insecticides most commonly used against defoliating soybean pests in the Southeast (VBC, CEW) contain permethrin. The permethrin group of insecticides provides up to a 98-percent immediate knockdown efficiency and residual effectiveness for up to 30 days after application. Methyl parathion is recommended to combat late season infestations of pod- and seed-feeding insects (SGSB, CEW), and furnishes up to a 95-percent knockdown efficiency on the day of application with little or no residual control action.

The economic component provides for net returns above variable costs as a measure of success of a chosen management strategy. Gross returns are calculated as soybean price in dollars per bushel times seed weight in bushels per acre. Costs are categorized as variable production costs other than insect control and irrigation costs, variable irrigation costs, variable pesticide costs, and a fixed cost for scouting. Table 1 shows variable production costs. Variable production costs, C_m, in dollars per acre excluding irrigation and insect control costs are calculated as

$$C_m = 111.50 + (2.98P_g + 9.20P_d)1.15 \qquad (5)$$

where P_g and P_d denote price per gallon of gasoline and diesel fuel, respectively. Equation 5 is derived from a northern Florida soybean cost-of-production budget prepared by Boggess. Variable irrigation costs per acre, C_i, are expressed as

$$C_i = I_t[5.834 - 0.101x + 0.0067x^2 + 3.5(P_d - 1.20)], \qquad (6)$$

Table 1—Variable production costs included in the SICM model

Source	Cost/unit[1]
Cost of field application of pesticides	$3.08/acre/application
Cost of employing an insect pest scout for a weekly field survey for the entire production season	$2.75/acre/season
Gasoline	98 cents/gallon
Diesel fuel	98 cents/gallon

[1]Costs reflect end of 1984 season conditions in southern Georgia. Source: Farm Economics Information Center, University of Georgia, Athens.

where I_t denotes total seasonal irrigation (cm) and x represents the amount of irrigation per application (cm) (*6*). Variable costs of pest control in dollars per acre are calculated by multiplying the number of applications per acre by the sum of chemical and application costs per acre.

The simulator was calibrated to produce Georgia Coastal Plain soil-type conditions and was driven by 9 years of weather data (1975-83), including temperature, rainfall, radiation, and pan evaporation rate collected at the Coastal Plain Experiment Station, Tifton, GA. Insect populations and crop status are recorded daily by the simulation routine. The insect population is monitored at 7-day intervals to mimic typical soybean-scouting practices. Pest control decision stages occur when insect populations reach damage threshold levels. A simulated control is then carried out to reduce insect populations in the crop according to insecticide effectiveness ratings.

The modeling procedure describes the interaction of irrigation and IPM as two interrelated technologies. Irrigation is specified to maintain a soil water content level which alleviates most water stress incurred by the plant and maintains a turgor threshold. The total package of IPM consists of strict compliance to Georgia's Cooperative Extension IPM recommendations, which include treatment for foliage-feeding insects when defoliation in the plant stand reaches 30 percent prior to full bloom. After full bloom and up through full pod-fill, the control threshold drops to 15-percent defoliation to protect the nutritive abilities of the leaf canopy. After full pod-fill, chemical control is recommended if defoliating pressure causes 25-percent leaf canopy loss.

Hatcher and others reported producer deviations, or what may be termed use of subsets of an IPM package (*9*). Their data indicate that producers enrolled in a Georgia IPM extension program adhered to extension recommendations 69 percent of the time thresholds were reached. When a recommendation to apply a chemical control was followed, producers applied an insecticide in a timely manner 41 percent of the time. However, 59 percent of producers who followed the treating recommendation applied an insecticide up to 7 days post-threshold, 3 days after the cooperative extension service's recommended last day of economic advantage.

The SICM model determined the effect of employing the total package of IPM, that is, following extension guidelines closely through the season, as well as a subset of the package (partially adopting), conditional on possessing irrigation. Data documenting the degree of specific insect infestations and dates when the influx occurred during 1972-84 were available from the Coastal Plain Experiment Station, Department of Entomology, Tifton, GA (*21*). The data include observations for the three insects modeled in SICM. Fifteen insect infestation and influx timing patterns as well as probability of occurrence for VBC, CEW, and SGSB, were developed from the data to describe the general nature of pest dynamics during those years. For instance, the combined probability of a light intensity VBC, CEW, and SGSB adult influx was 7 percent. A heavy and late influx of VBC combined with light intensity and expected inflights of CEW and SGSB adults had an 11-percent chance of occurring.

The simulator was run under dryland and irrigated conditions for each of the 15 insect infestation and timing patterns for each weather year under the assumption that a producer employs the total package of IPM technology. Under this deterministic approach, 270 iterations of SICM were required (15 insect patterns times 9 weather years times 2 water access options, dryland and irrigated).

We modeled producers' partial adoption of IPM by using a pseudorandom number generator to model compliance and then timeliness of threshold adherence. We performed 30 iterations of each of the 270 combinations of insect populations and weather data years, resulting in 8,100 runs of SICM. When an extension guideline population threshold was exceeded in the simulation, a random number was generated to determine whether IPM extension guidelines would be followed (random number $\leq$ 0.6900). When extension recommendations were followed, we used a second random number to determine when the model would apply a control up to 7 days post-threshold. When guidelines were not followed, the model enacted a control application on a predetermined calendar date (August 15) if the threshold was reached prior to this date. A threshold reached after the predetermined calendar date resulted in no control for defoliating insects. This process was repeated later in the season to determine adherence to threshold guidelines to control pod- and seed-feeding insects. Depending on the series of random numbers generated, the scenarios were ontime control, late control, predetermined calender application (Sept. 10), or no control for late-season insect pests. The expected value of net returns from these simulation runs represented producers' expected profits when following a partial adoption strategy. Yearly results were combined with the probability of any particular insect infestation pattern to derive overall summary statistics.

Results

Table 2 summarizes the simulation output for the IPM technology levels under dryland and irrigation technology conditions. Mean-variance (EV) analysis, in which the relative magnitude of these two distribution moments describing, in this case, a pest control-water access regime compared with an alternative regime, was unable to distinguish dominance between total and partial IPM under dryland production. The EV criteria indicate, however, that partial IPM dominates for the irrigation technology, probably because of the heartiness of the plant stand under irrigation and its resultant ability to resist yield-reducing insect damage with less insecticide. Total IPM generally incurs greater variable costs than a partial adoption strategy, decreasing net returns. In contrast, Gini mean difference (EG) (*24*, *22*) and expected value analysis indicate that total adoption of IPM under dryland

Table 2—Net returns, Gini mean, and dominance results for technology combinations

	Annual net returns/acre			Dominance[1]			
Technologies	Expected net profit	Variance	Gini mean difference	EV	EG	SSD	SDWRF
Dryland							
Total IPM	58.98	8962.44	23.22	0	Total	0	Partial
Partial IPM	57.62	8653.42	21.95				r > 0.0011[2]
Irrigated							
Total IPM	193.10	825.18	8.43	Partial	Partial	Partial	Partial
Partial IPM	198.38	807.03	8.65				r > 0[2]

[1] EV is expected value.
EG is Gini mean difference analysis.
SSD is second-degree stochastic dominance analysis.
SDWRF is stochastic dominance with respect to function.
[2] r denotes the Arrow-Pratt risk aversion coefficient, and 0 indicates that neither distribution dominates.

technology dominates, whereas the reverse is true with irrigation Expected value and EG decisional criteria assume risk neutrality or weak risk aversion, respectively Thus, risk neutrality or weak aversion indicate that differing levels of an applied prior technology will influence the effectiveness of a new technology, and hence, degree of adoption an increase in α, (the introduction of irrigation) results in a (IPM) declining in importance in terms of strict adherence

Employing the total IPM package under irrigated conditions proved inferior to adopting a partial IPM regime This probably results from extension IPM recommendations being tailored to a dryland production technology, which is the dominant production method in Georgia One possible hypothesis for this result is that partial adoption of IPM in conjunction with irrigation provides for an augmented information base as producers incorporate prior pest management experience along with select extension recommendations in determining a modified control program

Considering risk preference, results indicate that as risk aversion increases, partial adoption tends to dominate under a dryland technology Second-degree stochastic dominance (SSD) leads to indeterminate results and stochastic dominance with respect to a function (SDWRF), in which uncertain choices are defined by upper and lower bounds on an absolute risk-aversion coefficient This implies that only strongly risk-averse producers will partially adopt IPM under dryland conditions (*15*) Producers in other risk categories would be more willing to adopt a total IPM package under dryland conditions Obviously, if a new technology increases risk, the level of adoption will decline as the degree of risk aversion increases Partial IPM, with irrigation, however, dominates total IPM even with risk-neutral preferences Therefore, risk aversion does not totally account for partial adoption under irrigation Other variables, including socioeconomic characteristics and the success of previous technology adoption, will influence current adoption practices

Conclusion

The empirical results lend support to the hypothesis that variations in the use of existing technologies cannot be ignored when the extent of technology adoption is being investigated The results indicate that the degree of new technology adoption under differing technology bases may coincide with strong risk preferences, but that risk may not be the overriding element Our results suggest that strongly risk-averse producers with dryland technology may only partially adopt IPM We suspect that producers using irrigation recognize its influence in significantly decreasing the variation in yield and returns and, hence, diminishing the effectiveness of total IPM adoption, and would select partial adoption Thus, producers adopt the complete IPM package or subsets of the package depending to some degree on risk preferences and the level and complexity of production technologies currently in use Providing new technology information to producers should involve presentation of a complete technology "package" as well as appropriate modifications, or partial packages, to fit neatly into the producers' current production practices

Our results indicate that observations of varying adoption rates and methods among producers may be explained by differing technology bases or other factors as well as risk preferences This conclusion supports the general view emerging in the literature that the riskiness characteristic is not the overriding element in the IPM adoption decision, and may be overemphasized in other adoption literature as well

References

1 Antle, J M "Incorporating Risk in Production Analysis," *American Journal of Agricultural Economics* Vol 65, 1983, pp 1,099-106

2 Boggess, W G "Farm Budget Number 117232340 141 1, Irrigated Soybeans, North Florida " University of Florida, Gainesville, 1981

3 Byerlee, D , and E H de Polanco "Farmers' Stepwise Adoption of Technological Packages Evidence from the Mexican Altiplano," *American Journal of Agricultural Economics* Vol 68, 1986, pp 519-27

4 Caswell, M , and D Zilberman "The Effects of Well Depth and Land Quality on the Choice of Irrigation Technology," *American Journal of Agricultural Economics* Vol 68, 1986, pp 798-811

5 Clay, E J "Equity and Productivity Effects of a Package of Technical Innovations and Changes in Social Institutions Tubewells, Tractors and High-Yielding Varieties," *Indian Journal of Agricultural Economics* Vol 30, 1975, pp 74-87

6 D'Almeda P J , G D Lynne, and A G Smajstrla "A Users Manual for the Farm Systems Lab Irrigation Cost Generator " University of Florida Economic Information Report No 157, University of Florida, Gainesville, 1982

7 Farm Economics Information Center, Department of Agricultural Economics, College of Agriculture University of Georgia, Athens Personal communication

8 Feder, G , R E Just, and D Zilberman "Adoption of Agricultural Innovations in Developing

Countries A Survey," *Economic Development and Cultural Change* Vol 33, 1985, pp 255-98

9 Hatcher, J E , M E Wetzstein, and G K Douce *An Economic Evaluation of Integrated Pest Management for Cotton, Peanuts, and Soybeans in Georgia* University of Georgia Agricultural Experiment Station Research Bulletin 318, Nov 1984

10 Jenson, R "Adoption and Diffusion of an Innovation of Uncertain Profitability," *Journal of Economic Theory* Vol 27, 1982, pp 182-93

11 Johnson, S R , and G C Rausser "Systems Analysis and Simulation A Survey of Applications in Agricultural and Resource Economics," *A Survey of Agricultural Economics Literature* Vol II G G Judge, R H Day, S R Johnson, G C Rausser, and L R Martin (eds) Minneapolis University of Minnesota Press, 1977

12 Just, R E , and R D Pope "Stochastic Specification of Production Functions and Economic Implications," *Journal of Econometrics* Vol 7, 1978, pp 67-86

13 Kennedy, J O S *Dynamic Programming Applications to Agriculture and Natural Resources* New York Elsevier Applied Science Publishers, 1986

14 Leppla, N C , T R Ashley, R A Guys, and G D Butler "Laboratory Life History of the Velvetbean Caterpillar," *Annals of Entomological Society of America* Vol 70, 1977, pp 217-20

15 Meyer, J "Second Degree Stochastic Dominance with Respect to a Function," *International Economic Review* Vol 18, No 2, 1977, pp 477-87

16 Musser, W N , M E Wetzstein, S Y Reece, P E Varca, D M Edwards, and G K Douce "Beliefs of Farmers and Adoption of Integrated Pest Management," *Agricultural Economics Research* Vol 38, 1986, pp 34-44

17 Pingali, P L , and G A Carlson "Human Capital, Adjustments in Subjective Probabilities, and the Demand for Pest Controls," *American Journal of Agricultural Economics* Vol 67, 1985, pp 853-61

18 Rahm, M R , and W E Huffman "The Adoption of Reduced Tillage The Role of Human Capital and Other Variables," *American Journal of Agricultural Economics* Vol 66, 1984, pp 405-13

19 Rudd, W G "Population Modeling for Pest Management Studies," *Mathematical Bioscience* Vol 26, 1975, pp 283-302

20 Stinner, R E , R L Rabbs, and J R Bradley, Jr "Population Dynamics of *Heliothis zea* (Boddie) and *H virescens* (F) in North Carolina A Simulation Model," *Environmental Entomology* Vol 3, 1974, pp 163-68

21 Todd, J W , S H Suber, N Minton, T Reed, M Beach, and S Thompson "Development of Integrated Pest Management Systems in Soybeans " Annual reports for 1972-83 University of Georgia, Agricultural Experiment Station, Tifton

22 Wetzstein, M E , P I Szmedra, R W McClendon, D M Edwards "Efficiency Criteria and Risk Aversion An Empirical Evaluation," *Southern Journal of Agricultural Economics* Vol 20, 1988, pp 171-78

23 Wilkerson, G G , J W Mishoe, J W Jones, J L Stimac, D P Swaney, and W G Boggess "SICM, Florida Soybean Integrated Crop Management Model Model Description and User's Guide " Version 4 2 Report AGE 83-1 Dept of Agr Eng Inst Food and Agricultural Sci University of Florida, Gainesville, Nov 1983

24 Yitzhaki, S "Stochastic Dominance, Mean Variance, and Gini's Mean Difference," *American Economic Review* Vol 72, 1982, pp 178-85