Disease-Prediction and Economic Models for Managing Tomato Spotted Wilt Virus Disease in Lettuce

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ABSTRACT

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We devised disease-prediction and economic models that enable growers with lettuce fields affected by tomato spotted wilt virus (TSWV) to make management decisions early in the planting cycle. Conditional probability and linear regression models based on field data were used to examine disease incidence at harvest as a function of early disease incidence and cumulative thrips abundance. Early disease incidence was a better predictor of disease incidence at harvest than thrips abundance. A grower's economic return at various levels of TSWV incidence was estimated by incorporating expected disease incidence into an economic model.

Insect-transmitted viral pathogens of plants cause considerable crop losses worldwide (2,7,9,12). Tomato spotted wilt virus (TSWV) is an insect-transmitted plant virus that seriously affects crop production in both temperate and tropical regions (8,13). TSWV affects more than 200 plant species, including crops such as tomato, lettuce, pepper, peanut, tobacco, and several ornamentals (for example, *Chrysanthemum*, *Impatiens*, and *Gloxinia* spp.) (1,4).

TSWV is transmitted only by certain species of thrips (1,3). The western flower thrips, *Frankliniella occidentalis* (Perg.), is the predominant vector of TSWV found in Hawaiian lettuce fields (3,18).

In Hawaii, TSWV periodically causes severe losses in lettuce production (3,6). In some years, particularly in summer, TSWV destroys 50–90% of lettuce crops. Although effective control measures for limiting the spread of TSWV are not available, the ability to predict disease incidence at harvest would help growers to make rational management decisions. For example, predictions of high disease incidence made early in a planting cycle would let growers plow under unprofitable fields, thereby limiting production costs and reducing the buildup of TSWV inoculum in the field.

In plant epidemiology, the goal of forecast modeling is to minimize economic losses caused by plant diseases (16). Plant disease forecasting models have been widely used in crop protection to predict incidence of either pests or pathogens in the field (15). Forecasting models are especially important in agricultural systems such as lettuce in Hawaii, in which growers could benefit greatly from predictions of how much loss caused by disease can be expected at harvest.

With this in mind, models were developed from weekly data on TSWV disease incidence and cumulative thrips numbers that had been collected previously. Based on these data, we wanted to determine whether disease incidence at harvest could be predicted early in a planting cycle. The objectives of our study were to develop empirical models to predict TSWV disease incidence in lettuce at harvest and to predict profit at harvest by incorporating various levels of disease incidence into an economic model.

MATERIALS AND METHODS

Data collection. The forecasting models were based on TSWV disease incidence and thrips data collected primarily at two farms in Kula, Maui, between 1981 and 1985. At each farm, three replicated plots were established (6). All field plots were exposed to normal farming practices, such as pesticide applications and weeding. In Kula, lettuce growers subdivide their farms into sequentially planted blocks of 0.2–0.4 ha, with 15,000–20,000 lettuce seedlings per block. Seedlings are germinated in speedling trays (200 plants per tray), then transplanted to the field 4 wk after germination. Lettuce is harvested 7–8 wk after initial transplanting. In this report, the term "lettuce cycle" refers to the period from transplanting to harvesting. In the lettuce cycle, the transplanting week is week 0, the first week after transplanting is week 1, and so on.

Disease surveys were conducted weekly during 43 lettuce cycles. A lettuce plant was considered infected with TSWV if it had characteristic visual symptoms such as wilting, necrotic spots, and lesions on the leaves and midribs. In a previous study (6), both serology and mechanical inoculations on diagnostic plant hosts confirmed that typical disease symptoms are caused by TSWV. TSWV incidence was based on the average number of plants infected at the end of each lettuce cycle. During 30 of 43 lettuce cycles, data on thrips abundance were collected from yellow sticky cup traps as previously described (6). Periodic identification confirmed that *F. occidentalis* was the most abundant thrips collected during our study.

Conditional probability. Conditional probability was examined to provide a simple tool for predicting disease incidence at harvest from disease incidence early in the lettuce cycle (weeks 1–4). Disease incidence at harvest was divided into six classes: 0–10%, 11–20%, 21–30%, 31–40%, 41–50%, and >50%. Early disease incidence (weeks 1–4) was separated into three classes: 0–10%, 11–20%, and >20%. Using field data, we calculated the conditional probability for each combination of early disease incidence and for disease incidence at harvest. Four separate analyses were performed using disease incidence levels from weeks 1–4 (43 disease cycles).

Disease-forecasting model. A disease-forecasting model was designed to predict disease incidence at harvest (DH) using data on disease incidence, thrips abundance, or both. From the disease data, we knew the percentage of diseased plants (D) at a particular time (t) early in the lettuce cycle. For example, D_2 is the disease incidence at week 2. The change in disease (Y) was defined as the percentage of healthy plants at week t that became diseased by harvest. If we can estimate Y, then we can predict DH as follows: $DH = D_t + [(Y/100\%) \times (100\% - D_t)]$. For example, if $D_t = 20\%$

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and $Y = 50\%$, then $DH = 60\%$.

In disease surveys where both disease and thrips data were available, multiple linear regression analyses were used to estimate Y from early disease incidence data (D_t) and early thrips abundance (T_t). Thrips abundance was based on the cumulative average of thrips per trap for each week in the lettuce cycle.

Log transformation of D_t, T_t, and Y yielded a normal distribution of the data. Four separate multiple regression analyses were performed on the transformed data to test the relationship between independent variables D_t and T_t at weeks 1–4 and the change in disease (Y) (14). In addition to the multiple regression analyses, separate linear regression analyses were run between both independent variables (D_t and T_t) and the change in disease (Y) (14). We also generated 95% upper and lower confidence limits for each of the single linear regression analyses.

Economic model. An economic model was designed to estimate a grower's net return for a given block of lettuce (Rn). The model used the following equation: $Rn = Rg - Cf - Cv - Cm$, where Rg = gross return, Cf = fixed costs, Cv = variable production costs, and Cm = marketing costs (Table 1). Fixed costs included items such as rent, depreciation on buildings or equipment, interest, and taxes. Variable production costs were subdivided into preparation, field production, and harvesting costs. Field production and harvesting costs included inputs between transplanting and harvesting such as pesticides, irrigation, equipment use, and labor. Marketing costs were proportional to yield and were determined by multiplying each service charge—vacuum cooling (¢/kg), cooperative fee (% of profit), shipping (¢/kg), and sales tax (%)—by the total yield (kg) at harvest. All of these costs were based primarily on a previous analysis of head lettuce in Kula (10). Additional data were obtained from five lettuce growers on Maui.

The gross return is the product of yield × price. Maximum yield (assuming no losses) was determined as follows: yield = transplants/blocks × harvested plants/transplants × 0.6 kg/plant. For purposes of this analysis we assumed 17,000 lettuce transplants per block and 25 harvested plants per carton.

The ratio of harvested plants per transplant (i.e., proportion of maximum yield)

Table 1. Fixed, variable, and marketing costs associated with producing a block of lettuce in Maui, Hawaii

Type of costs	Amount
Fixed	
Depreciation on building and equipment	$10.00
Rent	5.00
Insurance	10.00
Taxes	2.50
Interest	7.50
Research	5.00
Miscellaneous	5.00
Total	$45.00
Variable	
Preparation	
Seeds	$ 25.00
Speedling trays	10.00
Seedling medium	100.00
Fertilizer	50.00
Fumigants	50.00
Pesticides	30.00
Water	45.00
Equipment and fuel	75.00
Labor	150.00
Miscellaneous	25.00
Subtotal	$560.00
Field production	
Pesticides	$ 75.00
Water	100.00
Equipment and fuel	75.00
Labor	400.00
Miscellaneous	25.00
Subtotal	$675.00
Harvesting	
Equipment and fuel	$ 25.00
Labor	150.00
Miscellaneous	25.00
Subtotal	200.00
Total	$1,435.00
Marketing	
Package carton	$1.35/carton
Vacuum cooling	1¢/lb
Co-op fee	12% of net
Trucking	$15.00/block
Shipping to Oahu	3½¢/lb
Sales tax	1.5%
Miscellaneous	$0.00

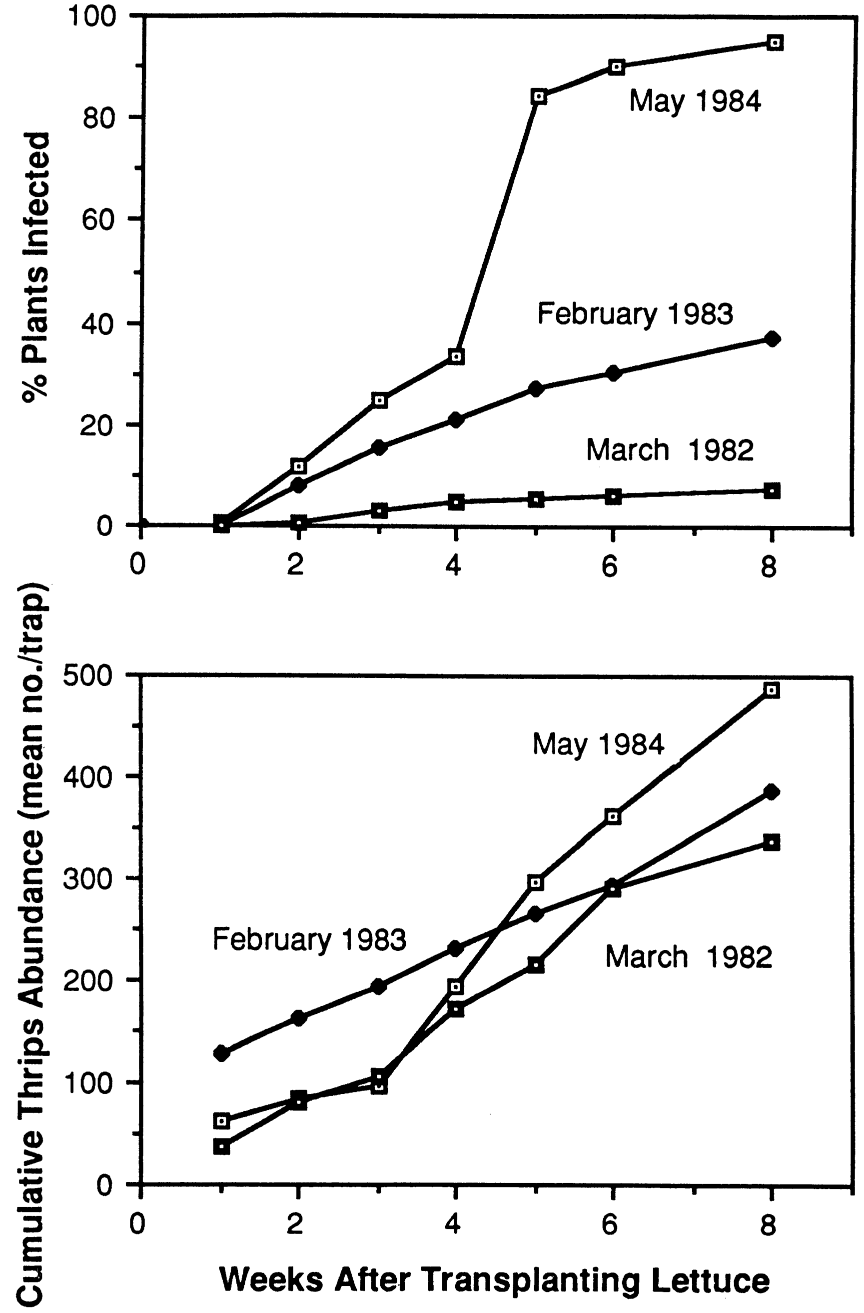

Fig. 1. Disease incidence and thrips abundance for three typical lettuce cycles in Kula, Hawaii.

can be expressed as 1 − proportion of crop lost. If TSWV is the only source of loss, then the proportion of maximum yield is $1 - (DH/100\%)$. A lettuce plant was not marketable if it had any characteristic visible TSWV symptoms.

Sensitivity analysis. A sensitivity analysis was used to evaluate the impact of disease incidence on economic return. Grower profits were projected as a function of variation in disease incidence at harvest (0–100%). Price at harvest was estimated from historical trends in price data. Price was systematically varied to examine alternative assumptions (12 and 15¢/kg). Costs used in the analysis are listed in Table 1.

RESULTS

Disease progression and thrips abundance. Figure 1 shows disease progression and cumulative thrips abundance for three typical lettuce cycles. TSWV disease incidence at harvest ranged from 0.33% to 97.5% (mean = 30.6% ± 4.8 SE, $n = 43$ lettuce cycles). Eleven of 43 cycles surveyed had greater than 50% incidence at harvest. Thrips abundance varied from four to 374 adults per trap per week (mean = 52.0 ± 3.8 SE, $n = 1{,}530$ traps). Cumulative thrips abundance at harvest ranged from 52 to 1,206 adults per trap (mean = 313.4 ± 41.2 SE, $n = 254$ traps).

Conditional probability. Disease incidence data from weeks 2, 3, and 4 were useful indicators of disease incidence at harvest, but data from week 1 were not (Table 2). Although disease incidence at harvest varied widely, disease incidence at week 1 was always less than 10% (Table 2). If disease incidence remained under 10% during weeks 2–4, however, then disease at harvest was less than 20% for most cycles (78% for week 2, 89% for week 3, 100% for week 4). If disease incidence was 11–20%, then the number of cycles in which disease at harvest exceeded 50% was 75% for week 2, 20% for week 3, and 10% for week 4. If disease incidence was greater than 20%, the number of cycles in which disease at harvest exceeded 50% was 75% for week 2, 83% for week 3, and 72% for week 4. In other words, if disease incidence was below 10% at week 2 or below 20% at week 3 or 4, then TSWV was rarely a serious problem at harvest. Conversely, if disease incidence exceeded 10% at week 2 or 20% at week 3 or 4, then TSWV was likely to cause serious loss (>50%) at harvest.

Regression analyses. Each of the four multiple linear regressions (from weeks 1–4) was significant, with 46–79% of the variation in change in disease (Y) accounted for by early disease incidence (D_t) and thrips abundance (T_t) (Table 3). However, most of that variation was accounted for by early disease incidence rather than by thrips abundance. Thrips abundance (T_t) represented a significant portion of the overall regression only at week 1 (Table 3).

Each of the eight single linear regressions was significant, with 17–71% of the variation in change in disease (Y) accounted for by early disease incidence (D_t) and 14–33% of the variation accounted for by thrips abundance (T_t) (Table 4). At week 1, thrips abundance was the best predictor of change in disease ($R^2 = 0.32$) (Table 4, Fig. 2). Compared with thrips abundance, early disease incidence accounted for more of the variation in Y at weeks 2, 3, and 4 ($R^2 = 0.57$, 0.71, and 0.68, respectively) (Table 4, Figs. 3–5).

Sensitivity analyses. Sensitivity analyses demonstrate how much a grower can expect in return (in dollars per block) as a function of disease incidence at harvest and lettuce price (Fig. 6). Assuming that no loss is caused by TSWV at harvest and the grower can get a price of 12¢/kg, the expected profit per block is $1,650; at 15¢/kg, the expected profit per block is $2,700 (Fig. 6). At the other extreme, however, if the loss caused by TSWV is 100% and inputs continue until harvest, then the grower loses $1,480 per block (independent of price, because yield = 0). As the lettuce price increases, a grower can lose more to disease and still make a profit at harvest. At 12¢/kg, a grower can break even (return = 0) with 52% disease loss at harvest. At 15¢/kg, a grower breaks even at about 64% disease loss (Fig. 6).

Table 2. Conditional probabilities of TSWV incidence at harvest given TSWV incidence at weeks 1–4

Early incidence (%)	Incidence at harvest (%) 0–10	11–20	21–30	31–40	41–50	>50	No.
Week 1							
0–10	0.35	0.21	0.07	0.09	0.02	0.26	43
11–20	0.00	0.00	0.00	0.00	0.00	0.00	0
>20	0.00	0.00	0.00	0.00	0.00	0.00	0
Week 2							
0–10	0.45	0.33	0.10	0.06	0.03	0.03	31
11–20	0.00	0.00	0.00	0.25	0.00	0.75	4
>20	0.00	0.00	0.00	0.12	0.12	0.75	8
Week 3							
0–10	0.58	0.31	0.08	0.00	0.04	0.00	26
11–20	0.00	0.40	0.20	0.20	0.00	0.20	5
>20	0.00	0.00	0.00	0.08	0.08	0.83	12
Week 4							
0–10	0.71	0.29	0.00	0.00	0.00	0.00	21
11–20	0.00	0.50	0.40	0.00	0.00	0.10	8
>20	0.00	0.00	0.00	0.07	0.21	0.72	14

Table 3. Multiple linear regression models for predicting change in disease (Y) using early disease incidence (Dt) and cumulative thrips abundance (Tt)

Weeks after transplant	Independent variables[a]	R^2	df	Equation	P
1	Disease (D_1) Thrips (T_1)	0.46 ···	26 ···	$\log Y = -0.10 + 0.74 \log D_1$ $+ 0.67 \log T_1$	0.0006 ···
2	Disease (D_2)	0.60	29	$\log Y = 0.49 + 0.88 \log D_2$	0.0001
3	Disease (D_3)	0.79	29	$\log Y = 0.02 + 0.98 \log D_3$	0.0001
4	Disease (D_4)	0.56	24	$\log Y = -0.25 + 1.06 \log D_4$	0.0001

[a] Only those variables significant at $P \leq 0.05$ were included in the overall regression.

Table 4. Single linear regression models for predicting change in disease (Y) using early disease incidence (Dt) and cumulative thrips abundance (Tt)

Weeks after transplant	Independent variables[a]	R^2	df	Equation	P
1	Disease (D_1)	0.17	42	$\log Y = 0.09 + 0.94 \log D_1$	0.0050
	Thrips (T_1)	0.32	29	$\log Y = -0.18 + 0.79 \log T_1$	0.0020
2	Disease (D_2)	0.57	42	$\log Y = 0.62 + 0.82 \log D_2$	0.0001
	Thrips (T_2)	0.33	29	$\log Y = -0.36 + 0.76 \log T_2$	0.0010
3	Disease (D_3)	0.71	42	$\log Y = 0.24 + 0.86 \log D_3$	0.0001
	Thrips (T_3)	0.27	29	$\log Y = -0.72 + 0.80 \log T_3$	0.0030
4	Disease (D_4)	0.68	37	$\log Y = -0.02 + 0.91 \log D_4$	0.0001
	Thrips (T_4)	0.14	24	$\log Y = -0.96 + 0.78 \log T_4$	0.0300

[a] Only those variables significant at $P \leq 0.05$ were included in the overall regression.

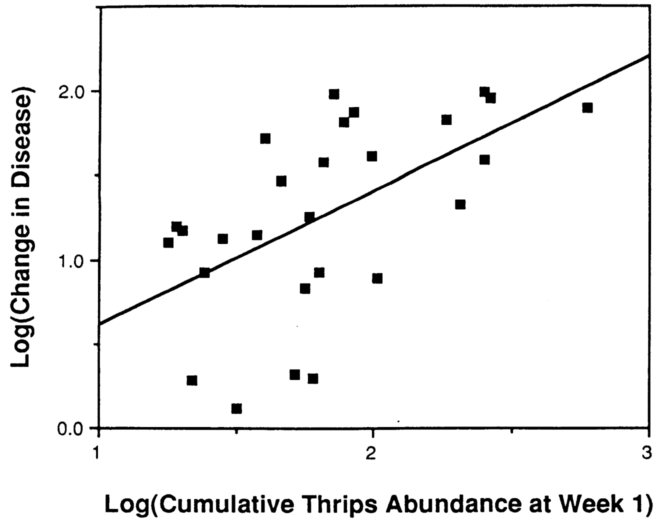

Fig. 2. Relationship between thrips abundance at week 1 and the change in disease (log-transformed). Regression equation: log $Y = -0.18 + 0.79 \log T_1$ ($R^2 = 0.32$).

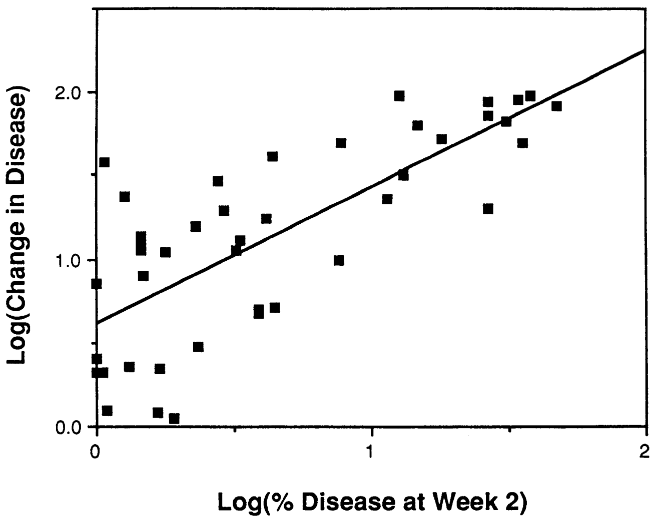

Fig. 3. Relationship between disease incidence at week 2 and the change in disease (log-transformed). Regression equation: log $Y = 0.62 + 0.82 \log D_2$ ($R^2 = 0.57$).

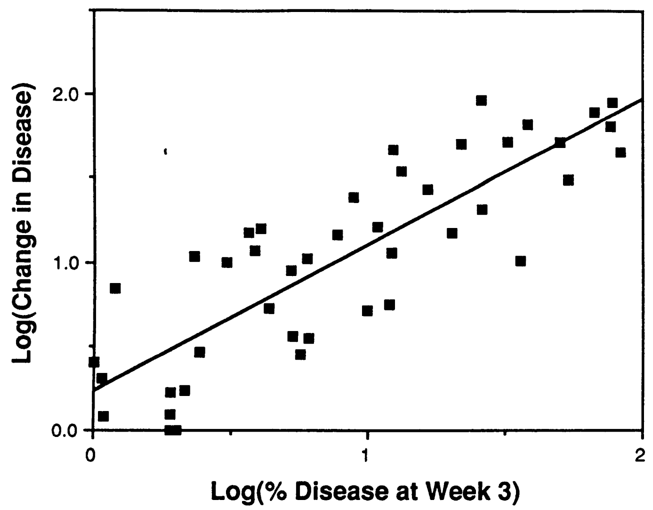

Fig. 4. Relationship between disease incidence at week 3 and the change in disease (log-transformed). Regression equation: log $Y = 0.24 + 0.86 \log D_3$ ($R^2 = 0.71$).

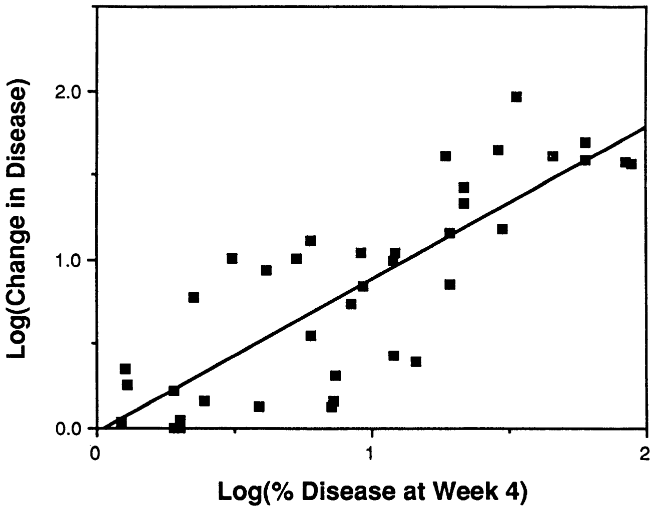

Fig. 5. Relationship between disease incidence at week 4 and the change in disease (log-transformed). Regression equation: log $Y = -0.02 + 0.91 \log D_4$ ($R^2 = 0.68$).

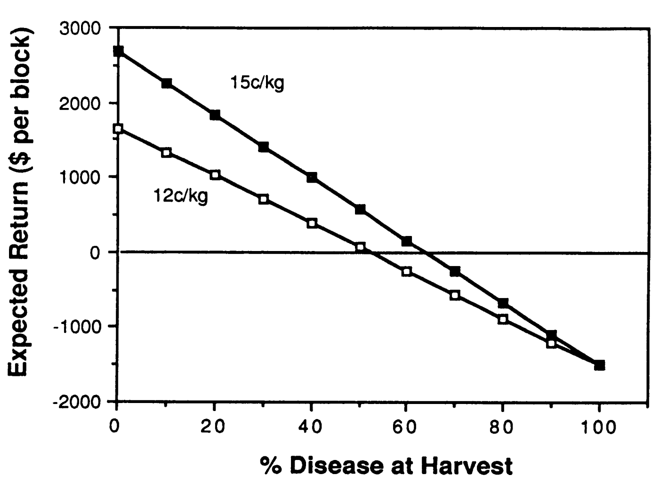

Fig. 6. Sensitivity analysis demonstrating the relationship between disease at harvest and a grower's expected net return (dollars per block).

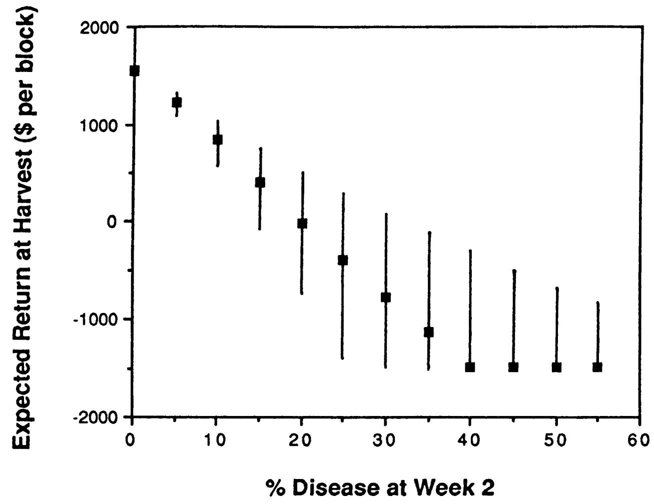

Fig. 7. Relationship between disease at week 2 and expected return at harvest (dollars per block at 12¢/kg) with 95% upper and lower confidence limits.

DISCUSSION

Our data show that disease incidence at harvest is significantly associated with early disease incidence and early thrips abundance. The use of thrips abundance to predict disease incidence at harvest lets the grower make predictions before disease symptoms appear. Because the incubation period for TSWV is approximately 1 wk, disease symptoms cannot be seen in newly transplanted lettuce for at least 7 days—unless the seedlings were infected before being placed in the field. Consequently, the use of thrips abundance levels during the first week is critical to predicting losses at harvest when disease expression is either extremely low or not present. Once symptom expression begins, disease incidence (determined by symptomatology) is an excellent means for estimating disease incidence at harvest (Table 3). The best prediction method would be to collect thrips data for the first week and then collect disease incidence data for weeks 2, 3, and 4.

The activities of viruliferous thrips play a vital role in the spread of TSWV. Previous studies show that only a small percentage of thrips collected in the Kula farm area are viruliferous (Cho et al, *unpublished*). An enzyme-linked immunosorbent assay (ELISA) method has been recently developed to detect TSWV in single thrips (5). Our study did not address the question of whether the spread of TSWV was caused mainly by viruliferous thrips migrating into the lettuce farms from reservoir hosts or by their movement from plant to plant within a field. Vanderplank (17) suggested that TSWV fits a simple-interest model because "spotted wilt virus was entering fields from without" and plant-to-plant dissemination within the tomato fields could not be detected. Pennypacker et al (11), examining the same data, suggested that the spatial pattern of TSWV fits a logistic model that assumes plant-to-plant movement of the pathogen does exist. Once thrips begin to colonize a lettuce block, they feed and reproduce easily on lettuce and seem to prefer infected lettuce to healthy plants (19). Hence, spread of TSWV within a field from infected lettuce to healthy plants is certainly feasible. Our data include some patterns of disease spread that fit a logistic model and others that fit a simple-interest model.

The models we have described are useful in both short-term and long-term planning. The key decision in short-term planning is whether to continue inputs during a particular lettuce cycle; the key long-term decision is whether lettuce can be grown profitably after allowing for typical yield losses caused by TSWV.

When planning for the short term, a grower would stop inputs if expected net return after continued inputs is projected to be lower than that resulting if inputs are discontinued. For example, assume that by week 2 a grower has spent \$773 (fixed costs [\$45] + preparation costs [\$560] + 2 wk of field production costs [\$168]) (Table 1). If inputs stop at week 2, the grower loses \$773. To justify continuing the inputs after week 2, the grower's expected net return at harvest must be greater than −\$773. The sensitivity analysis shows that if the price of lettuce is 12¢/kg, the grower's expected net return is −\$773 at a disease incidence at harvest of 77% (Fig. 6).

The conditional probability table (Table 2) shows that if disease incidence is at or below 10% at week 2, the chance of disease incidence at harvest exceeding 50% is only 3%; in this case, inputs should be continued. If disease incidence at week 2 is above 10%, however, the conditional probability table does not provide a definite recommendation.

The single linear regression forecasting model (Table 4) predicts 77% disease incidence at harvest when disease incidence at week 2 is 30%. Therefore, if disease incidence at week 2 is greater than 30%, expected net return is less than −\$773. Knowing this, the grower should stop inputs to reduce losses and plow the field under to limit the source of inoculum.

The 95% confidence limits give an indication of the variation that can be expected. If disease incidence at week 2 is 20%, the grower's expected return ranges from \$506 to −\$732 at 12¢/kg (Fig. 7). Since the lowest expected return within this interval (−\$732) is still less of a loss than the −\$773 already accrued by week 2, the grower should continue field inputs. However, if disease incidence at week 2 is 25%, then the grower's expected return ranges from \$335 to −\$1,395 (Fig. 7). In this case, the grower's net return might exceed the −\$773 accrued at week 2; other factors besides return (such as uncertainty in market price at harvest or the feasibility of trying to limit the field source of inoculum so that adjacent or future plantings may be less affected by TSWV) might be taken into consideration before deciding to continue field inputs or plow the field under.

In long-term management planning, the decision to remain in production is based on typical disease pressures, expected market prices, and whether profit goals set by the grower can be met. In most years, lettuce production in Kula has been profitable. In only in a few cases would it have been economically justified to discontinue production. Among the 43 lettuce cycles we surveyed, the mean disease incidence at harvest was 30.6%. Using the economic parameters in our sensitivity analysis, the expected return at 30.6% loss at harvest would be \$683 at 12¢/kg and \$1,535 at 15¢/kg (Fig. 6). However, profitability may deteriorate in the future; we have seen an alarming rate of TSWV incidence spread in other lettuce-growing areas in Hawaii. Furthermore, the cost of producing a single head of lettuce in Hawaii is expected to increase due to rising labor, fuel, and pesticide costs, while California is expected to continue to supply the market with lettuce at competitive prices.

The uniqueness of our economic and disease prediction models is their practical application at the farm level. Because diseased lettuce plants are easily observed in the field, initial disease incidence can be monitored by growers, scouts, or extension agents. The conditional probability table is a tool that a grower can readily use for short-term decisions (i.e., whether to continue to the next week) and as an early indicator of whether additional disease monitoring is warranted. The regression model is more complex—but also more precise—than the conditional probability anaylsis. A flexible, user-friendly computer program has been developed that incorporates both models and predicts both yield loss and expected profit on the basis of different prices, block sizes, and input costs. Individual growers can incorporate their own estimates to project individual profitability. This program can be obtained free of charge by sending a formatted diskette to the senior author.

Our study demonstrates some productive avenues for improving control of TSWV. Perhaps more important, it has unified biological and economic information into a conceptually based quantitative framework that can be applied immediately in the management of TSWV disease.

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