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IMBEDDING DYNAMIC RESPONSES WITH IMPERFECT INFORMATION INTO STATIC PORTAITS OF THE REGIONAL IMPACT OF CLIMATE CHANGE

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It is becoming increasingly clear, at least on a theoretical level, that modelers of the potential impacts of climate change must impose that change upon the world as it will be configured sometime in the future rather than confine their attention to considerations of what would happen to the world as it looks now. Initial baselines which focus on current circumstances are certainly worthwhile points of departure in any study, of course, but the truth is that social, economic, and political systems will evolve as the future unfolds; and careful analysis of that evolution across a globe experiencing changes in its climate must be undertaken, as well. In the vernacular of the analysts' workroom, while it may be interesting to try to see what would happen to "dumb farmers" who continue to do things as they always have regardless of what happens, it is critically important to evaluate the need for any sort of policy response to climate change in a world of "smart farmers" who will have observed the ramifications of climate change and responded in their own best interest.

Taking this point from the theoretical to the practical can, however, be problematical. Models of climate change are growing increasingly complex - so complex, in fact, that it is frequently beyond the scope of the modelers to run even "interesting" time dependent scenarios of what might happen; and capturing the full flavor of the uncertainty with which we view the future with full-blown probabilistic analyses appears to be even more impossible. There are simply too many random variables and too much structure in the typical model to accommodate even abbreviated Monte Carlo techniques. The best that can be expected in many cases is a short series of portraits of social and economic structures drawn for specific times in the future with the actors having reacted in some, usually equilibrium based way to some altered, but static new climate.

It must be recognized even in these constrained analyses, however, that future experiences will be time dependent. Future responses to those experiences will be dynamic adjustments informed not only by what is known at the present time, but also by what will have been learned as the future has unfolded. Reactions at any point in time will not necessarily be perfect reflections of how to best respond to the new and/or emerging climate of that time, though. They will, instead, be imperfect reactions based upon a learning process which will have taken the most recent manifestations of that climate as imprecise evidence that the climate <u>might</u> have changed. The longer the new climate has been in force, the less imperfect will be the perceptions of the change, but perfect recognition of the new climate and perfect reaction to its ramifications cannot be expected. Just as it is incorrect to analyze the impact of change in a world of "dumb farmers", it is inappropriate to fill a model of the future with "clairvoyant farmers" who are too smart.

The issue to be confronted here, then, is one of trying to create a methodology with which to capture the imprecision of adaptation within a static and time specific portrait of the future without running a complete set of probabilistically weighted scenarios over immediately preceding period. Were it possible to draw such a portrait, incorporating this imprecision in the actions of its players, would certainly aggregate to a more accurate reflection of what the social and economic evolutionary process will have achieved. It would therefore be an improved foundation upon which to base subsequent exploration of the need for policies designed to accomplish either some additional adaptive response or the frequently hailed dramatic and preemptory averting response.

The present paper will not attempt to describe a general methodology. It will, instead, begin the development of such a methodology by suggesting a means by which imperfect information might be translated into incomplete and imprecise reaction for a single, very specific decision - the choice that farmers face to switch crops, or at least their mix of crops, in response to growing evidence that the climate appears to be changing. To that end, Section I will present an outline of a utility based decision model and demonstrate the type of individual reaction functions that it supports in an uncertain world. Section II follows with an arbitrary, numerical illustration designed specifically to explore the structure of these reaction schedules. The theoretical underpinnings for a crop switching decision will thereby be established.

The third section of the paper will turn practical, applying the same structure to data produced by the agriculture team involved in a thorough, methodologically focused analysis of the resource and economic impact of potential climate change on a four state region located in the center of the United States.[2] A specific farm, defined by locational parameters and confronted with a specific crop switching decision in light of growing evidence that the "dust-bowl" climate of the 1930's has returned in the wake of greenhouse induced climate change, will be examined. Farm reaction given 5 and 25 years of experience with the new climate will be postulated, and methods for aggregating individual farm responses into regional pictures of an agricultural sector in flux will be proposed.[3]

Concluding remarks will finally propose some general insight which can be supported from the lessons of the agriculture modeling. There is reason to believe that these insights could turn out to be quite robust; agriculture is, after all, high on virtually every list of economic sectors likely to sustain significant impacts from greenhouse induced climatic change.[4] Moreover, the general notion which motivates the approach proposed here is a simple one - if the entire model is too complex to incorporate uncertainty and imperfectly informed decision-making throughout, then construct an overall impact portrait of a socio-economic system in flux by (i) introducing uncertainty into the simpler, sub-modules of the larger model, (ii) investigating response mechanisms in these simpler contexts, and (iii) summing these responses across sub-modules in an economically consistent way.

I. Crop Decisions in a Utility Framework.

Let a farmer's utility be given by

$$u(y) = \{y^{\beta+1}/(\beta+1)\}, \qquad (1)$$

where y reflects the profit derived from farm activity and the parameter "β" is the usual Arrow-Pratt measure of relative risk aversion.[5] Farm profits are assumed to be derived from a mix of two crops (crops 1 and 2 denoted x_1 and x_2) according to

$$y(a, x_1, x_2) = ax_1 + (1-a)x_2, \qquad (2)$$

where x_i represents the profitability per hectare of crop i and the parameter "a" represents the proportion of farming activity, expressed in area cultivated, devoted to crop 1. The two crops can, in fact, represent specific crops or specific rotations. The only critical point here is that they capture alternative uses for a given farm or farmland. Scale does not matter, either, given the structure of equation (1). The farm can, therefore, be assumed to cover only one hectare for convenience; but the parameter "a" can be interpreted more generally as the proportion of farmland within a given homogenous region devoted to crop 1.[6]

Now add uncertainty to the model by representing the joint distribution of profitability of crops 1 and 2 from year to year under the existing climate by $f_o(x_1, x_2)$, and the analogous distribution under a potential new and different climate by $f_n(x_1, x_2)$. These economic yield distributions can be assumed to be reasonably well known. They are, perhaps, the result of simulation exercises based upon crop yield models which currently exist or as they will exist after being refined by climate related research undertaken in the future.[7] It is there respective applicability which is in doubt in the face of possible climate change.

Since farmers, in making their decisions, are likely to look to experts and agricultural stations to provide information about the relative likelihood that the climate has changed, it is appropriate to let π_t be an index of the farmer's subjective perception at time t that the climate has indeed changed so that $f_n(x_1, x_2)$ and not $f_o(x_1, x_2)$ applies. Notice carefully that this structure implies that farmers understand the implications of possible climate change on their yields but are unsure of whether or not it has occurred.

Experts have provided the $f_j(x_1,x_2)$ distributions to their satisfaction, in other words, but are in disagreement over the value assumed by π_t. It takes 30 years to define a climate change, and experts have been left to try to digest the content of series of annual weather patterns in the meantime.

The farmer's decision at any point in time can now be characterized as one of selecting a^* which maximizes the expected utility derived despite uncertain profitability,

$$EU[y(a)] = (1-\pi)\int\int u[y(a,x_1,x_2)]f_o(x_1,x_2)dx_1dx_2 + \pi\int\int u[y(a,x_1,x_2)]f_n(x_1,x_2)dx_1dx_2,$$

subject to the constraints defined in equations (1) and (2). Algebraic manipulation of the appropriate first order condition reveals that

$$\frac{(1-\pi)}{\pi} = -\frac{\int\int[a^*x_1+(1-a^*)x_2]^\beta[x_1-x_2]f_n(x_1,x_2)dx_1dx_2}{\int\int[a^*x_1+(1-a^*)x_2]^\beta[x_1-x_2]f_o(x_1,x_2)dx_1dx_2}$$

$$\equiv k\{a^*,\beta\}. \qquad (3)$$

The interior structure of equation (3) implicitly defines a reaction function $a^*(\pi,\beta)$ by requiring that

$$\frac{(1-\pi)}{\pi} = k\{a^*(\pi,\beta),\beta\}. \qquad (4)$$

For each and every degree of risk aversion, therefore, equations (3) and (4) define a correspondence between the perceived likelihood of climate change and the desired allocation of farming effort between crops 1 and 2.

II. An Illustrative Example.

The meaning and significance of the class of reaction functions characterized in equations (3) and (4) are perhaps best understood when cast in terms of a specific, but qualitatively realistic illustration. Climate change is, for example, expected to bring hotter and dryer weather to the midwestern portion of the United States.[8] Crop yields and associated profits from farming could easily fall, as a result, even as they become more variable from one season to the next. Any illustrative example meant to display possible effects on and responses from the agricultural sector of that region should therefore reflect both trends in its construction.

Suppose, to that end, that profits per hectare from x_1 and x_2 were distributed from year to year according to

$$x_1 \sim N(10.0;2.0) \text{ and} \qquad (5a)$$

$$x_2 \sim N(9.0;3.0) \qquad (5b)$$

prior to any change in climate and would be distributed according to

$$x_1 \sim N(8.0;2.0) \text{ and} \qquad (5c)$$

$$x_2 \sim N(7.5;2.5) \qquad (5d)$$

in the aftermath of such a change. These distributions show that mean profitability for both crops would fall and become more variable if the climate were to change.[9] Since the x_1-x_2 ratio of mean yields and t-statistics would both fall in the wake of climate change, moreover, it is clear that crop 1 would be more severely effected both in terms of lower yields and increased variability.

The change in means reflected in equations (5a) through (5d) would certainly make crop 2 relatively more attractive in the new state of nature (i.e., the new climate), but lower relative expected yields alone would not be enough to inspire a change in farming activity. Crop 1 would still dominate even given the new climate if the ranking were judged solely on the basis of average profitability (note that 8.0 > 7.5 just like 10.0 > 9.0). No adjustment in the mix of crop should be forthcoming, therefore, unless risk aversion placed some weight upon the expected utility cost of increased relative variability.

Figure 1 displays this tradeoff by portraying the results of applying equation (4) to the distributional structure of equation (5). The reaction schedules reflected there for various Arrow-Pratt values of relative risk aversion are the product of simulation exercises which assumed perfect correlation across x_1 and x_2 <u>within any year</u> for both states of nature. They show the full range of correspondence between the subjective probability that the climate has changed and the proportion of farming effort and land devoted to crop 1.

Note, to take one of the more extreme case shown in Figure 1, that a farmer with low risk aversion (RRA = -0.8) would devote 100% of his or her effort to x_1 until it became nearly certain that the climate had changed; even with perfect certainty that the new state of nature had arrived, in fact, the proportion of effort devoted to x_1 would fall only to 60%. This case clearly illustrates the general notion that low risk aversion allows considerable weight to be given to the persistent higher average profitability of crop 1. On the other side of the coin, a farmer with a strong aversion to risk (RRA = -8.0) would specialize in crop 1 under the current climate but would respond quickly and dramatically to even the hint of climate change; effort devoted to x_1 would plunge to 20% with only a 10% perceived chance that the new climate had arrived and would disappear completely when experts were 30% certain.

The intermediate cases reflected in Figure 1 are, of course, far less definitive. Given any probability of climate change, Figure 1 shows that almost any level of response could be expected depending upon the degree of risk aversion of the farmer in question; the specifics of this illustration were, in fact, chosen so that this full range of reactions would emerge. Were it possible to restrict the potential values assigned to the relative risk aversion parameter, perhaps by prescribing initial conditions based upon the relative importance of crops 1 and 2 under current conditions, then a more limited range of anticipated responses might be achieved; but specifying risk aversion is only part of the problem. Regardless of the limits placed upon the risk parameter, applied work based upon the modeling of Section I must also be supported by methods designed to reflect subjective views of the likelihood of significantly altered climate. Section III will address both issues - the need to specify ranges for the risk aversion parameter and the subjective probability that climate has changed - in the context of an application to one type of farm captured in the MINK Study.

III. Application Within the MINK Study.

The agricultural portion of the MINK Study has incorporated extraordinarily detailed micro-analyses of typical farms from eleven MLRA's (Major Land Resource Areas) scattered across the four state region. The map portrayed in Exhibit 1 displays their coverage. Together, these eleven sub-regions can be used to span all of the important crop rotations, soil types, distinct weather patterns, and irrigation practices found in the MINK states. One farm in MLRA 109, for example, is included as a representative of farms located in southern Iowa and northern Missouri which currently grow soybeans and corn in bi-annual rotation without extensive irrigation. Experts consulted by the MINK study group have suggested that sorghum would be substituted for corn in the rotation if greenhouse induced climate change were to return the dust-bowl weather patterns of the 1930's to the region.[10] It is this substitution decision which will be examined here as an illustration of how the utility structure of Section I might be applied within a holistic regional impact assessment.

The EPIC agriculture yield model was first run for the target farm in MLRA 109 (henceforth Farm 109) using 30 years of actual daily weather experience recorded there from 1951 through 1980. These runs suggest, in the context of current price expectations and commonly accepted cost structures, that the annual profitability per hectare of growing corn in the soybean-corn rotation given current climatic conditions is distributed by

$$c_o \sim N(112.9;137.8); \qquad (6a)$$

the corresponding distribution of the annual profitability of growing sorghum under current conditions is, meanwhile,

$$s_o \sim N(27.2;73.5). \qquad (6b)$$

Repeating the EPIC simulation exercise for three successive decades of dust-bowl climate defined by actual weather patterns observed in MLRA 109 from 1930 through 1939 suggest comparable analog profitability distributions for corn and sorghum given by:

$$c_n \sim N(-20.2;120.7) \text{ and} \qquad (6c)$$

$$s_n \sim N(24.3;81.6), \qquad (6d)$$

respectively.

Corn obviously dominates under the current climate for all but the most risk averse farmer; indeed, sorghum is not now an important crop in MLRA 109. Were the change in climate perfectly recognized, however, the switch to sorghum would obviously pay dividends; the experts are right. In a world of uncertainty and imperfect recognition, though, the questions posed here remain. How sure must farmers be that the climate has changed before they decide to switch crops? And how sensitive is that decision to their relative aversion to risk?

The answers to these questions, specific to Farm 109 at least, can be gleaned from Figure 2. The reaction schedules drawn there were derived by applying the content of equations (2) and (3) to the distributions recorded in equations (6a) through (6d).[11] They are the product of simulations which again assumed perfect correlation of profitability for corn and sorghum within any single year in both states of nature.[12] Notice that complete specialization in corn dominates in all five cases when there is no perceived chance that the climate has changed. For all but the smallest aversion to risk, however, even a small perceived chance that a new climate has arrived precipitates a significant response. A 10% chance, more specifically, inspires at least a 60% shift to sorghum for the other four schedules, and 80% adjustments for three of the relative risk aversion values depicted. Perhaps more importantly, though, complete specialization in sorghum is anticipated in four cases when it is perceived to be 60% likely that the dust-bowl has returned.

Turning now to the issue of the subjective likelihood that climate has changed, the issue is specifying a reasonable range for the "π_t" parameter. Suppose that agriculture stations base their climate announcements on the basis of 30 year moving averages of annual rainfall.[13] A portrait of the year 2010 under dust-bowl weather might reasonably assume that the citizens of MLRA 109 will have experienced 5 years of associated weather and thus rainfall. Drawing 5 years of weather at random from the climate of the 1930's and letting the previous 25 years be drawn similarly from the current climate, the 30 year moving average would assign a minuscule probability value to the null hypothesis that average annual precipitation at Farm 109 would match the 1930's average. If experts then quoted this probability value as the likelihood that the change had occurred so that $\pi_{2005} \approx 0.0$, then Figure 2 shows that no shift to sorghum in the rotation should be expected to have occurred. Aggregation across MLRA 109 assuming the "dumb farmer" baseline scenario would then be appropriate.

If a portrait were drawn for the year 2020 with 15 years of dust-bowl weather having been experienced, however, the story would change. Drawing 15 years of weather from both the 1930's and the current climate, the 30 year moving average would assign a probability value of 0.34 to the null hypothesis. If experts then announced a 34% probability that the climate had changed, then Figure 2 shows a significant shift to sorghum. Aggregation across the MLRA assuming that between 75% and 90% of the farming activity were devoted to sorghum and the rest remaining in corn could, as a result, be advanced as a more accurate representation of the subregion in flux - responding to the imperfect but growing realization that the new climate had arrived. It would, in other words, paint a better portrait of the region than either the "dumb farmer" snapshot with everyone still growing corn or the "clairvoyant farmer" vision with everyone switched to sorghum.

Clairvoyance would, however, be appropriate ten years later. Applying the same procedure to the year 2030 with 25 years of experience with dust-bowl conditions would again assign a minuscule probability value, this time to the alternative null that the climate had not changed. A value of 0.0% might then be assigned to π_{2030}, and Figure 2 shows that a total shift to a soybeans-sorghum should have been accomplished throughout MLRA 109.

Notice, finally, that application of the decision model to all three years produce different, but clear pictures of how much response might be expected without severely limiting the range of risk aversion. This clarity is, of course, the fortunate result of bunching among the reaction schedules reflected in Figure 2 - bunching which was, in turn, generated by the dramatic changes in the profitability distributions associated with moving to the dust-bowl experience. Less dramatic change would produce more ambiguous results, but would also be less important.

Translating the reactions just noted for the years 2010, 2020, and 2030 into expected profitability statistics can, however, suggest that the implications of their incorporation into the aggregate economic picture of the MINK region can prove to be extremely significant. Taking the distributions recorded in equations (6a) through (6d) as given and accepting the modeler's 20-20 vision that climate has indeed changed, notice that no switch to sorghum with 5 years experience by 2010 can be expected to reduce average profits for farms represented by Farm 109 by over \$133 per hectare (from \$113 to -\$20). Summing across all such farms in MLRA 109 would then show considerable economic damage - damage which would filter down to other sectors of the MINK region through macroeconomic feedbacks. Assuming an 80% switch to sorghum by 2020 would raise average profits from -\$20 per hectare to \$15 per hectare [the 20%-80% weighted sum of \$-20 from corn and \$24 from sorghum] and reduce the overall economic impact by 26%. Minimum losses from the new climate, equalling \$89 per hectare given complete specialization in sorghum, would represent a 33% reduction in overall cost that would be accomplished by 2030. Clearly, better information that could speed the adjustment process would pay large dividends not only for the individual farmer, but also for the MINK region as a whole.

IV. Concluding Remarks.

The motivation behind the simple, utility based decision analysis described here is purely practical. The current debate over how and when to respond to the threat of greenhouse induced climate change must be informed by modeling exercises which cast the range of potential impacts of that change against the world as it will evolve as the future unfolds. It is not enough to study the possible effects on today's world because individuals, institutions, and even markets will adapt, at least to some degree, to change as it occurs. There is, as a result, a fundamental need for analysts who are evaluating the relative efficacy of exogenous policy responses to the threat of climate change to incorporate "moving" pictures of how societies and economies react endogenously, if imperfectly, to its potential ramifications.

Models designed to support this type of policy analysis have, unfortunately, grown so large and complex that they cannot easily accommodate this demand for incorporating endogenous, intertemporal adaptation. They are typically too large to allow the iterative generation of the necessary time series trajectories of important state variables; they tend to focus, instead, on static portraits of large systems which can be produced for specific benchmark years scattered at regular intervals into the future. In the process of drawing these portraits, therefore, modelers are left with the task of deciding what sort of adaptation might have taken place by each of those benchmark years on an almost ad hoc basis.

The present paper accepts this modeling constraint, but suggests that it might actually apply only across entire system taken as a whole. Systems approaches to limate change impacts usually rely on the integrated sum of many sub-modules to produce their aggregate results; and these sub-modules are usually smaller, easier to manipulate, and come closer to portraying the behavior of the actors who will, in fact, be doing the adapting.[14] Even if it were impossible to conduct probabilistic analyses of adaptation decisions across the entire system, might it not therefore be the case that specific decisions, made over time despite imperfect recognition of extent to which climate has changed and fundamental uncertainty about its ultimate impact, could be investigated? Consistent integration of these imprecise decisions over the larger system could then add some appropriate sense of flux and transition to the static portrait of the aggregate system.

The theoretical utility structure presented here suggests that the answer to this query can be affirmative. Its application to farmers' decisions to switch crops in the face of the return of severe dust-bowl weather reaffirms that answer for the MINK impact assessment methodology. It should be noted, however, that careful attention was paid in the development of the MINK Study to the process of aggregating the micro impacts of climate change into catalogs of macroeconomic consequences. This emphasis on bottom up design certainly makes it easier to accommodate the entire range of sparse, partial, or complete reactions which can emerge from micro decision analyses under uncertainty. Difficult as it is to wade through the details of a bottom-up construction, the resulting ability to look at sectors in flux adds a whole new distributional dimension to impacts analysis. Glimpses of who responds too early and who responds too late can show who looses a little and who looses alot and provide some insight into the equity and efficiency consequences of new information.

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* The reference from RFF for the MINK study will be added when available; consult RFF directly in the meantime.

ENDNOTES

1. Helpful comments were offered during the early stages of this work by Al Liebetrau and Michael Scott of Pacific Northwest Laboratory, Norm Rosenberg, William Easterling and Mary McKenney of Resources for the Future, and Thomas Malone of Sigma Xi and St. Joseph's College in West Hartford, CT. Funding support was provided by the United States Department of Energy under contract DE-AC06-76RL01830 and Connecticut Sea Grant.

2. The MINK Study is a regional impact assessment which concentrated on a four state region (Missouri, Iowa, Nebraska, and Kansas) which was sponsored by the U.S. Department of Energy in 1988 and completed late in 1990. It is the product of a collaborative effort of Resources for the Future, Oak Ridge National Laboratory, Pacific Northwest Laboratory and Sigma Xi, and focused much of its attention on issues of methodology. The analytical structure employed evolved into a system of many components (notably agriculture, energy, forests and water) with many interactions and many interdependencies. Each interaction was defined fundamentally in terms of regional macroeconomic relationships which were, in turn, derived directly from the microeconomic foundations of the sectors involved.

3. The MINK study is designed to produce portraits of the impacts of climate change in the years 2010 and 2030. It will be assumed, therefore, that dust-bowl conditions appear in the region beginning in the year 2005.

4. Nordhaus [1990], for example, used the 1989 U.S. EPA Report to Congress to review the national income accounts in search of sectors which might be effected by greenhouse induced climate change. Only agriculture, forestry, and fisheries fell into the severely impacted category. Moderately impacted sectors included construction, water transportation, real estate, energy, and recreation.

5. The Arrow-Pratt measure of relative risk aversion is a curvature notion, defined precisely by $R(y)=yu''/u'$; for the schedule given in equation (1), then, $R(y)$ is constant and equal to β. It is proportional to the insurance which an individual would purchase to avoid a random lottery on income, so larger values for β (in magnitude since $\beta<0$) correspond intuitively to larger aversion to taking risks. See Arrow [1970].

6. More than two crops can be accommodated by simply extending equation (2) through some arbitrary x_n. The joint probability distributions for the $\{x_1,...x_n\}$ could be more complex, of course, but the procedure outlined here would still be perfectly applicable.

7. EPIC is a biomass yield model developed at Texas A & M University and adapted in consultation with Resources for the Future to accommodate climate change with CO_2 fertilization. Evolution of such models in the future would be based upon actual experience and some reflection of an associated learning process. Current likelihood weights can be used to incorporate what might be learned along alternative scenarios into a weighted set of $f_t(x_1,x_2)$ distributions. See Yohe [1990].

8. See Schneider and Rosenberg [1988] for some introduction to the uncertainty with which such a statement can now be made.

9. Variability, here, is measured in terms of the usual notion of t-statistic.

10. Absent any information from global circulation models which specifies climate, much less weather, for regions as small as MINK, the MINK Study has used actual weather from the dust-bowl years as a climate analog representation of the

potential impact of greenhouse induced warming. It was therefore possible to run the agriculture yield simulations given actual weather experiences and contrast the results with yields that are supported by the current climate and associated weather. It was also possible to provide diversity in weather within the region that is nonetheless consistent with a clear change in climate.

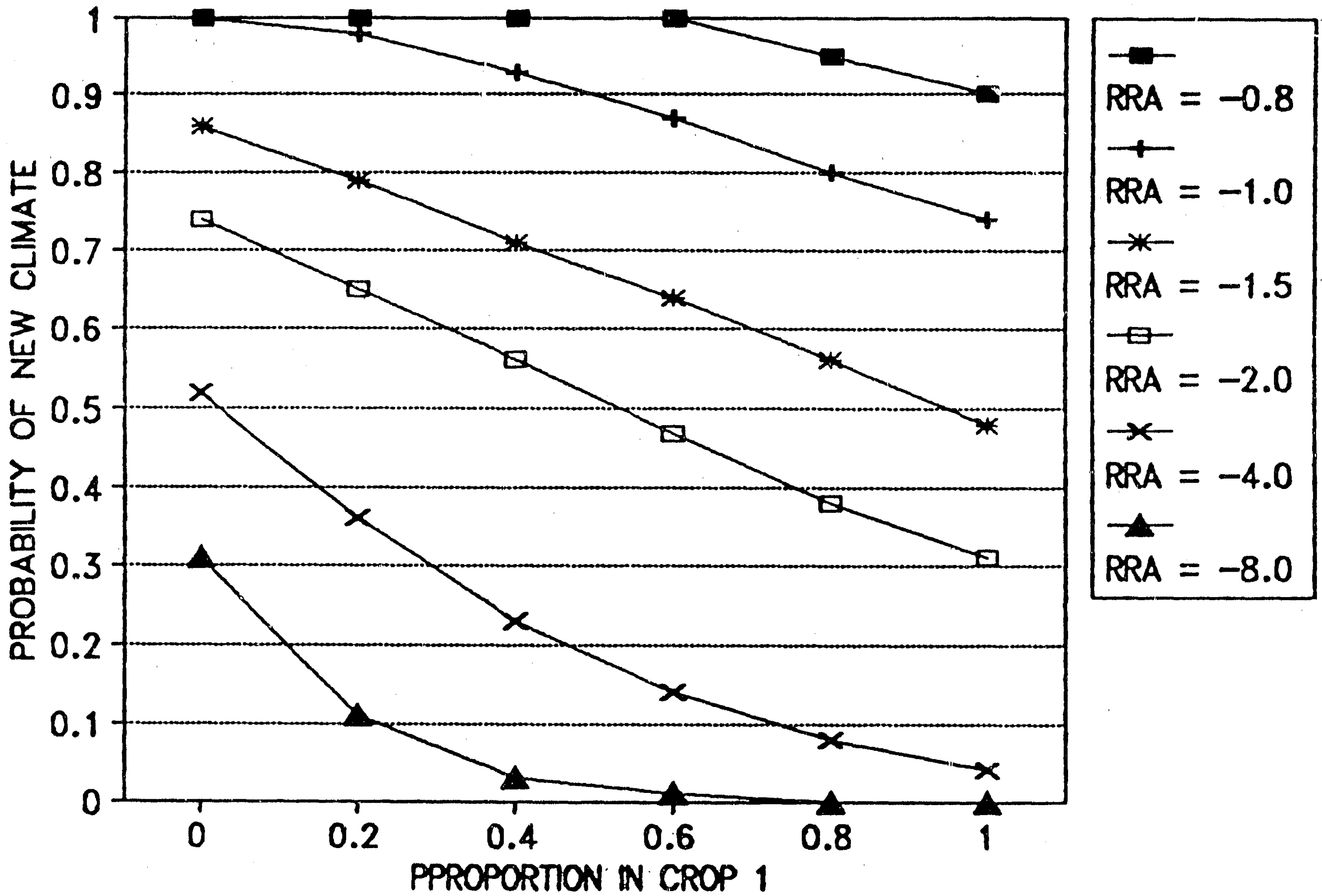
11. Variable profitability in each case was measured against a positive base income without loss of generality so that the utility structure of equation (1) could be applied even with the negative returns which emerge in equations (6). The notion of relative risk aversion is uneffected.

12. The actual correlation coefficient of profitability in both states of nature lies above 0.98, so assuming perfect correlation does little violence to the reality of the EPIC simulation results.

13. It is widely recognized that it takes 30 years to define climate, so 30 year moving averages are, at least, reasonable tools to assess changes in climate.

14. See Liebetrau and Scott [1990] for a discussion of how to exploit this modular structure in conducting uncertainty analysis.

FIGURE 1



1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
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PROBABILITY OF NEW CLIMATE
0
0.2
0.4
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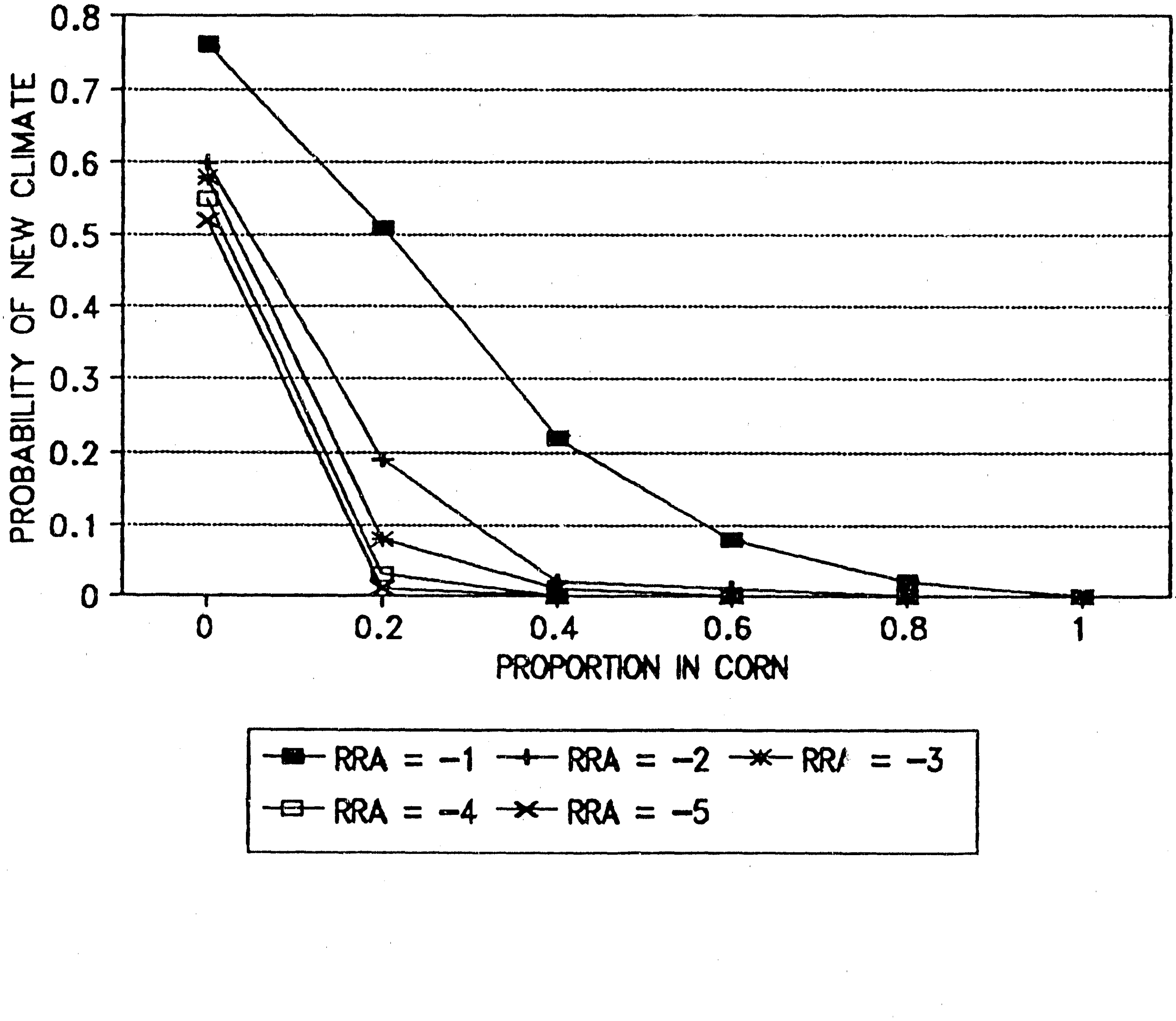
0.8
1
PPROPORTION IN CROP 1
RRA = −0.8
RRA = −1.0
RRA = −1.5
RRA = −2.0
RRA = −4.0
RRA = −8.0

FIGURE 2



0.8
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PROBABILITY OF NEW CLIMATE
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PROPORTION IN CORN
RRA = -1
RRA = -2
RRA = -3
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RRA = -5

MLRAS SELECTED
FOR STUDY
IN THE
MINK REGION

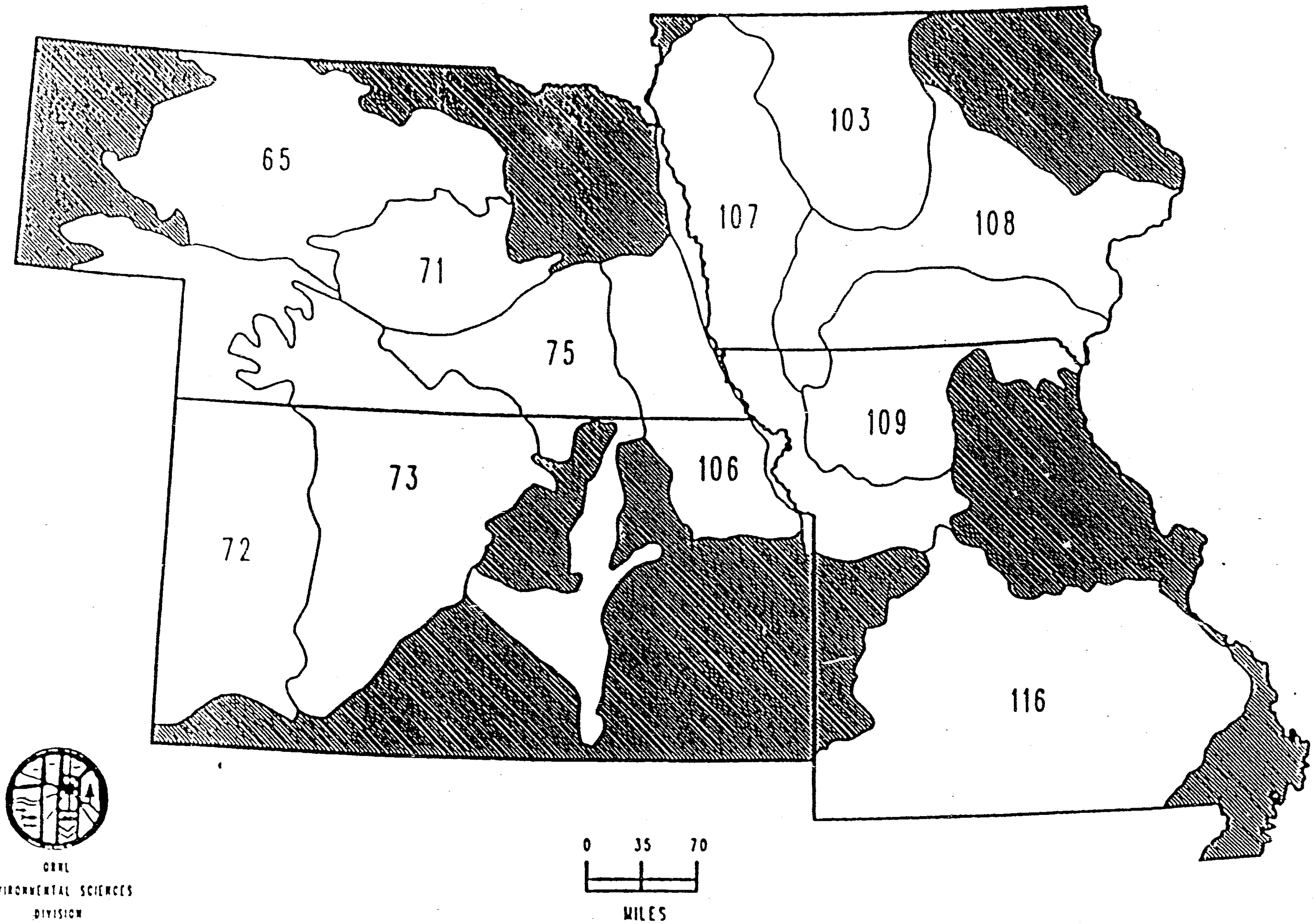

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EXHIBIT 1

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