The Analysis of Environmental Thresholds

by

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Abstract

Environmental changes are the key variables in the explanation of environmentally induced violent conflict. Regrettably, the question what environmental changes are and how they can be detected has hardly been addressed. In this article, we define what environmental thresholds are, how they can be detected using mathematical properties of response functions in the case of time-*independent* responses, and illustrate the statistical detection of such thresholds in the case of time-*dependent* responses. In case of time-independent responses, the threshold detection is based on the analysis of continuity and differentiability of the response function. In case of time-dependent responses, the simulations of a biogeochemistry process model (BIOME-BGC) are used to generate vegetation productivity response to different levels of atmospheric CO_2. Then, a statistical method is utilized to analyze time series of vegetation productivity and to detect its thresholds.

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1. Introduction

Do increasing anthropogenic emissions of greenhouse heating gases change the global and local climate beyond what we would expect in the absence of human interference? Which exposure to carcinogens leads to the development of cancer in animals and humans? As diverse as these questions may appear, they pose the same underlying question: Does an increase in a dose lead to a discernible response? Are any thresholds involved in the relationship between dose and response? Furthermore, in the field of environment and security, the question has arisen if environmental degradation leads to violent conflict. Although humans are likely to adapt to environmental conditions over time, rapid adverse *changes* in environmental parameters may substantially enhance the probability of violent conflict. This implies that only if environmental changes have arisen, any violent conflict which may have occurred could be attributed, wholly or in part, to environmental causes (Sprinz 1998). To uncover the existence of environmental changes, a systematic approach to detect environmental thresholds is needed.

Defining environmental thresholds has a long tradition in the natural sciences (Aber and Melillo 1991; Winner and Greitner 1991) and in human health risk assessment (e.g., Rosenthal et al. 1992). Most generally, an environmental threshold can be described as a point of a natural system (vegetative, aquatic, etc.) at which the essential characteristics of the natural system's present state change dramatically or where this impacts socio-economic systems (see also Parry et al. 1996, 2). Some environmental thresholds and the results of surpassing them are well known. For example, many plants cannot extract water from the soil with matric potentials more than -1.5 MPa. This point has been termed the *wilting* point. When the soil water is depleting and soil matric potential is approaching the wilting point, the plant starts wilting and may die. Alternative conceptions of thresholds include the notion of "surprise", i.e., discontinuities or outlier events as a response to changes in forcing agents such as greenhouse gas concentrations (Schneider and Root 1996).

In the toxicological and pharmacological literature, functional relationships between increasing amounts of a causing agent (dose, such as carcinogens), are related to the onset of adverse health effects (response, such as tumors). The resulting dose-response functions are used in the setting of occupational health standards and are subject to a lively academic and public debate. In the regulatory context, thresholds have been defined as "the dose of the toxicant below which no adverse effects will occur" (Rosenthal et al. 1997, 55). If such thresholds actually exist remains the subject of much controversy. While some authors suggest that thresholds do exist at non-zero levels of a dose (e.g., Schaeffer 1981), others doubt that thresholds can be generally derived (Beyersmann 1986, 33), and some authors suggest that neither can be shown for carcinogens (e.g., Cohrssen and Covello 1989, 95). Despite the scientific controversy about the existence of environmental thresholds, limit values are set for occupational health risks. These values also reflect subjective valuation of risks and economic aspects considered by regulators (Winter 1986).

In toxicology, experimental setups are normally used to determine the dose-response function that is often derived from experiments with animals. By determining the "no observable adverse effect level" and the "lowest observable adverse effect level," it is concluded that the (absolute) threshold must lie between those two doses (Rosenthal et al. 1997, 55). In order to introduce a safety factor for human protection, polynomial regression is used to make inferences about *low* dose-response values from *high* dose-response relationships - the latter are rarely empirically observed (Graham et al. 1997; Schaeffer 1981, 479-480). The particular choice of degree of a polynomial for statistical analysis and the substantive implications of such choices remain a contentious issue since empirical observations are lacking and the results are assumed to be suitable for interspecies comparison, e.g., between mice and humans (e.g., Graham et al. 1997). While this approach may detect a threshold dose for any non-zero response, it does not provide information about thresholds across the much broader functional domain of the dose-response relationship.

A range of methods has been proposed to derive thresholds. Ruck (1990) distinguished four approaches to thresholds in ecotoxicological research, with the three latter approaches relying on dose-response functions. In the empirical-frequentistic approach, the threshold is determined as a percentile (e.g., 95% percentile) of the dose. As the author admits, this "provides no evidence of a real risk" (Ruck 1990, 2). By contrast, in the empirical-normative approach, a permissible target response dose is set and statistical methods are used to determine a percentile interval of doses. Alternatively, the inductive-deterministic approach uses a fixed transfer coefficient to relate pre-set target responses to a point estimate of the permissible dose. To be a credible method, the relationship between dose and response is not allowed to be complex. Finally, in the inductive-stochastic approach, a tolerated response is combined with estimated frequency distributions of the transfer coefficient to yield a frequency distribution of the *dose* - thereby allowing uncertainty to be incorporated in the computation of the permissible dose (see Ruck 1990). While the first method does not identify any risk or threshold, the last three approaches rely on the existence of a predetermined response level to infer permissible doses. None of these approaches derives environmental thresholds in a non-arbitrary way or delineates a way to set the permissible response level without resorting to normative judgment.

Perhaps the most promising route to defining environmental thresholds has been taken in the field of detecting thresholds for acidification. By constructing a simple mass balance equation for acidifying substances and the chemicals offsetting adverse effects, a critical load or level of acidification is derived (Posch et al. 1995). While this method has provided good guidance for informing decision-makers on regulating transboundary air pollution in Europe, the model has not yet been more generically applied to other environmental domains.

In conclusion, dose-response relationships provide the common basis for deriving environmental thresholds. While thresholds are normally defined as the lowest dose which yields a non-zero response, this concept omits the possibility of thresholds occurring across the full range of the dose-response function. In addition, regulatory practice often uses normative judgment to set response levels, which are used to infer the permissible level of the dose. This article provides an alternative approach by deriving thresholds based on mathematical properties of dose-response functions for time-*independent* responses and a statistical method for time-dependent responses. In the case of time-independent responses, the threshold detection is based on the analysis of continuity and differentiability of the response function. In the case of time-*dependent* responses, the simulations of a biogeochemistry process model are used to generate vegetation productivity response to different levels of atmospheric CO_2. Then, a statistical method is utilized to analyze time series of vegetation productivity and to detect its thresholds.

2. Methods

2.1. Introduction

As the preceding review suggests, two different approaches can be chosen to derive thresholds. First, a permissible response level is set and the correspondent permissible maximum dose is inferred from the dose-response function. Alternatively, a second approach focuses on the functional properties of the dose-response relationship and applies mathematical criteria in order to search for thresholds. While the first approach is often used as a practical measure in the field of public health, it often does not detect thresholds per se but reflects the composite of experimental evidence extrapolated to human beings, the preferences of regulators and various interest groups, and a collective decision-making process. As a consequence, the same experimental evidence can yield different regulatory results which depend, e.g., on the degree of safety margin regulators wish to reach. Except for "absolute thresholds" (see below), the first approach yields results of limited value which suggests that a mathematically derived alternative would provide a less ambiguous foundation for the diagnosis of thresholds, in general, and environmental thresholds, in particular.

2.2. Mathematical Derivation of Thresholds

Dose-response functions provide a succinct summary of the relationships between incrementally increasing doses (e.g., increasing levels of atmospheric CO_2 concentration) and responses (e.g., environmental performance indicators). While the analysis of thresholds can be applied to a multitude of "dose variables" which, in combination, generate a response or set of responses, we will concentrate on a single dose (exogenous) and a single response (endogenous) variable for simplicity of exposition.

Three different approaches can be subsumed under the mathematical approach to define thresholds, namely the search for (i) absolute thresholds, (ii) discrete steps (discontinuous functions), as well as (iii) the analysis of continuous functions.

The most prominent role in the writing on thresholds plays the *absolute threshold*, i.e., the "smallest detectable stimulus" (dose) which yields any non-zero level of response (The New Encyclopedia Britannica 1992, vol. 25, 498) (see (D_1, R_1) in Figure 1). As shown further above, this approach plays an important role in regulating hazardous substances. Regrettably, it covers only a limited part of the full functional range of the dose-response function, and is a special case of discontinuous functions (see below).

Important properties of functions, such as the dose-response functions, include continuity and differentiability across the range of values of interest to the researcher. A function is said to be "continuous if its graph has no breaks" (Simon and Blume 1994, 31).[1]

[1] More formally, a "function f: $D \rightarrow R^1$ is continuos at $x_0 \in D$ if for any sequence $\{x_n\}$ which

Thus, a lack of continuity in a function points to thresholds. Functions which take the shape of "staircases" are the most illustrative example and belong to the class of "jump discontinuity" (Bronsthein and Semendyayev 1985, 232): Each step represents one threshold of the response dimension (see thresholds at (D_1, R_1), (D_2, R_2) and (D_3, R_3) in Figure 1).

As Figure 1 shows, the *discontinuities* of the function are maintained for extended intervals across the dose axis. If the discontinuity only pertains to a single point x_0 or a few of these, then this "removable discontinuity" (Bronsthein and Semendyayev 1985, 232) should not be regarded as a threshold since the limits of the underlying function taken around the removable discontinuity would have pointed to a continuous function.

However, even continuous functions may have thresholds. For example, the function of $f(x) = |x|$ has a negative slope of -1 for all $x < 0$, takes on the value of zero for $x=0$, and has a positive slope of +1 for all $x > 0$. As the sign of the slope changes at $x = 0$, we might infer that this is a threshold. More generally, if the first derivative (a measure of the slope or steepness) of a function cannot be taken at particular points x_0, these points qualify as thresholds.

While all differentiable function are continuous, these functions may have thresholds, namely *local extreme points*. By finding the parts of a function where the first derivative is zero (i.e., the slope is zero) and the second derivatives (representing the *change* of the slope) are negative (positive), local maxima (minima) can be derived. As in the case of the noncontinuous differentiable function $f(x) = |x|$, a switch in the sign of the slope points to thresholds (see Figure 2 for a local minimum (D_1, R_1) and local maximum (D_2, R_2)).

In this section, we have dealt with the static case, i.e., we assumed that in an experimental design, incrementally increasing doses generate values on the response scale. However, many (quasi-)experiments have a temporal structure which allow us to follow the trajectory of a particular dose over time. Since many studies of global environmental change use scenario techniques to provide answers to "what (happens) if (we change the dose or score of a particular exogenous variable)" questions, the analysis of thresholds has to be applied to such a time series design. Thereby, the responses take on a time dimension that is not commonly found in the toxicological or pharmacological literature. As a result of the time-dependent properties of the response, complete sets of responses have to be compared to different levels of the dose. The following section will provide an introduction how generic statistical time series techniques can be utilized to analyze thresholds in temporal designs.

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converges to x_0 in D, $f(x_n)$ converges to $f(x_0)$" (Simon and Blume 1994, 32).

2.3. Diagnosing Thresholds of Time Series Data

It is rarely the case that observed data in research on environmental and global environmental change are available for long time periods. Often, such data suffer from lack of intercomparability over time or are simply not (yet) available. Even if observed data exist, they often do not encompass a wide variation of the dose (e.g., atmospheric CO_2 concentration, pollution levels, etc.) - thereby substantially limiting the observed range of the dose-response function. Therefore, we illustrate our approach with data generated by a simulation model, which allows us to systematically compare the time series response trajectories generated by a wide range of doses.

Assuming that a simulation model is an appropriate, yet simplified representation of the real world, we can generate time series of responses to a constant dose. For example, with the model introduced in the following section, we simulate forest growth over time with different levels of atmospheric CO_2 concentration. By allowing the dose variable (atmospheric CO_2 concentration) to vary systematically, we can undertake structured comparisons of vegetation productivity responses. In this time series approach, we cannot literally apply the mathematical criteria introduced in Section 2.2, however, we can systematically compare the response trajectories for two particular responses. In particular, if two trajectories are the same, the *ratio* for any observation is equal to one for comparable time steps, and first differences of the ratios of both trajectories will yield zero values. Any systematic and persistent structure deviating from such a pattern indicates that we are witnessing a change in the state of the environment between the two doses under investigation. This approach resembles the discontinuity approach to detecting thresholds. To undertake structured comparisons, we used univariate time series analysis which models the structure of time-dependent data.[2]

The goal of univariate time series analysis is the modeling of the time-dependent structure found in the data, including trend components, the influence of observation onto their own successors (autoregression), and the covariation of error processes with their own successors (moving averages). Upon correct specification of the time-dependent structure,

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[2] Introductions to time series analysis can be found in Greene (1997, ch. 18) or Harvey

we should observe "*white noise*," i.e., the errors remaining after estimation are of zero mean, constant variance, and uncorrelated over time (Greene 1997, 824). As a prerequisite for further analysis, the data series have to be *stationary*, i.e., the observations are independent of the particular point in time, their variances are constant and independent of the particular point in time, and the covariation between observations is only a function of the lag between them (Greene 1997, 828).

To make a series (of responses) stationary, persistent trend elements - such as an average increase or decrease in the level of responses over time - have to be controlled for. This is often accomplished by taking differences between adjacent observations. The "order" of differencing or integration reflects how often such differencing has to be undertaken. While overall trend components are very informative, they are equivalent to the linear slope component of a series, which is continuously differentiable - and does not point to a threshold (see Section 2.2). By contrast, the constant term of an autoregressive process allow us to diagnose if successive observations exhibit an additional trend component once the series is stationary.[3] In particular, if a ratio of two time series has been differenced once and the time series analysis points to a statistically significant non-zero constant, we suggest that a threshold has been passed in the comparison of the two doses. This constant represents a significant deviation from the expectation that subsequent observations are unrelated to prior observations. If we compare multiple series of observations and determine their degree of autoregressive structure, different orders of autocorrelative processes point to (weaker) thresholds passed by the underlying doses, which generated the observations. By contrast, the constants of moving averages point to changes in the mean of a series generated by autocorrelations among the (white noise) errors over a finite period of time. Modeling moving averages actually smoothes the series, and thresholds are not associated with such processes.

The particular statistical approach used is the ARIMA method pioneered by Box and Jenkins (1984) which determines the order of autocorrelation, the order of integration by differencing the functions, and the order of the moving average processes. In the following, we will briefly introduce the model that generates the time series equivalent of the dose-response function.

(1993).

3 A coefficient of zero for the autocorrelative term itself points to a "random walk" - clearly the absence of a threshold.

2.5. Modeling and Data Sources

Given the evidence of rising carbon dioxide concentration in the atmosphere (Keeling et al. 1995) and increased vegetation activity in certain regions of the globe (Myneni et al. 1997), alteration of the carbon cycle requires special attention and may lead to irreversible changes in vegetation activity that may subsequently affect humans. In view of the challenge posed by climate change, we will attend to a particular aspect attracting substantial interest, namely net primary productivity (NPP)[4]. Vegetation NPP is the largest carbon flux from the atmosphere into the biosphere. NPP characterizes the amount of atmospheric carbon converted into biomass per time period, and it can be useful to estimate forest growth and crop yields. More specifically, it is measured as the difference between gross photosynthetic productivity (atmospheric carbon uptake by plants) and autotrophic respiration (carbon release resulting from plant growth and tissue maintenance). Estimation of NPP is much more problematic over landscapes as compared to a single plant. Nevertheless, NPP estimation at a landscape scale is more relevant to this study of environmental security and the study of regional and global environmental changes. Ecosystem models and satellite observations are used to estimate NPP over landscapes (Hunt at al. 1996, Running et al. 1996, Prince 1995). A modeling approach allows us to separate effects of various environmental factors (temperature, rainfall, nitrogen deposition, etc.) on NPP and to investigate the responses to changes in those factors.

In this study, the ecosystem process model BIOME-BGC (Hunt et al. 1996; Running and Hunt 1993; Waring and Running 1998) was used to estimate vegetation productivity around the globe. The BIOME-BGC model simulates three vital biogeochemical cycles: carbon, nitrogen, and water within an ecosystem. NPP was calculated in terms of gas exchange, i.e., as a difference between gross photosynthetic production and autotrophic respiration.

The BIOME-BGC method for NPP estimation is a key to understanding the empirical results of this study. This estimation results from the interactions of numerous environmental controls simulated by the model. Consequently, climate, nutrient availability, and vegetation type influence NPP through controls on *both* photosynthesis and respiration processes. In the

[4] The method applied in the data analysis is generic to the problem.

BIOME-BGC model, the gross photosynthesis (*GPP*) limited by climate and nutrients was calculated as:

$$GPP = f\,(T, VPD, SW, SRAD, CO_2, LAI, LEAFN),$$

where T is the air temperature, VPD is the vapor pressure deficit, SW is the soil water content, $SRAD$ is the solar radiation at the top of canopy, CO_2 is the carbon dioxide concentration in the atmosphere, LAI is the leaf area index, and $LEAFN$ is the leaf nitrogen concentration. Air temperature, leaf, and root nitrogen contents controlled autotrophic respiration (R_a):

$$R_a = f\,(T, LEAFN, ROOTN),$$

where $ROOTN$ is the nitrogen concentration of roots. Thus, the BIOME-BGC model is able to capture effects of a number of abiotic (temperature, vapor pressure deficit, soil water, solar radiation, and CO_2 concentration) and biotic (leaf area index, leaf, and root nitrogen contents) controls on NPP.

This model was used to undertake a series of analyses of NPP for 200-year intervals (response) for varying levels of CO_2 concentrations in the atmosphere (dose). All other factors of the model were kept constant throughout the analysis. For each run, the model was initialized with a particular level of atmospheric CO_2 concentration, which was kept constant throughout the run. Since the model was initialized so as to simulate growth of a new forest in each of the runs, the output for the first 100 years does not represent a steady state. This was only accomplished toward the end of this period, and we included only the model output for the second 100-year simulation in our statistical analysis.

The BIOME-BGC model allows us to choose any grid cell across the world for analysis. For this prototypical investigation of environmental thresholds, we picked a grid cell typical of boreal forests in Sweden (latitude = 64.5° North and longitude = 19.5° East) since Sweden has extensive coniferous forests as well as is a major producer and exporter of forest products. The range of CO_2 concentrations to be included in our calculations was determined on two grounds. First, the lowest level of CO_2 which the BIOME-BGC model can still accept for computational reasons is about 16% (55.8 ppm CO_2) of *present* CO_2 concentrations in the atmosphere. It serves as a lower bound for our dose levels.[5] Second, the multiple of present levels of CO_2 concentrations (350 ppm CO_2 or 1x CO_2) should be very large so as to include a broad interval of doses. Small multiples of 1x present CO_2 are customarily involved in analyses of global climate change; this provides confidence that 10x

[5] Preindustrial levels of CO_2 are 275 ppm (or .79x present) CO_2 levels.

present CO_2 concentrations will constitute a reasonable upper bound for the range of doses.[6] The resulting raw data are displayed in Figure 3.

As Figure 3 indicates, low levels of CO_2 let NPP increase only slowly during the second century, whereas we observe decreasing trends for all concentrations higher than 0.5 x CO_2.

Two analyses were undertaken with these data. First, we used present levels of CO_2 (1x CO_2) as a reference and computed the ratio of NPP relative to this trajectory for varying levels of CO_2. If any thresholds can be found, they will reflect environmental thresholds relative to present levels of the dose. This procedure is justified because present environmental performance is often chosen as a benchmark for comparisons in environmental and social modeling. This procedure, however, will only answer the question at which interval of doses the state of the environment is changing relatively to the present conditions, i.e., at maximum, a threshold is found each below and above the present dose level of CO_2. To make more detailed inferences regarding the existence of environmental thresholds, we compute, second, the ratios of NPP for adjacent ratios of CO_2 concentrations. As a consequence, we will be able to detect whether additional thresholds exist.

3. Results and Discussion

The first set of analyses involved the ratios of NPP relative to 1x CO_2 (see Figure 4). The trajectories show a generally positive trend for doses smaller than 1x CO_2 and a negative trend for doses larger than 1x CO_2. In addition, the data show a pronounced 3-year cycle, because BIOME-BGC was run for a *constant* 3-year climate input repetitively. Consequently, the data have to be differenced once overall and twice for the 3-year seasonal component.

The statistical analysis shows that the constant term for the equations is positive for a dose of 0.16 relative to 1x CO_2, remains zero for doses between 0.25 and 1x CO_2, and turns negative for doses higher than 2x CO_2 (see Table 1). Given the order of differencing of the

[6] Throughout the analysis we assume that the model computes correct results. The goal of this research is not to validate the BIOME-BGC model which simulates response of forest productivity to changing atmospheric carbon dioxide concentration but to demonstrate the merit of our method to detect thresholds.

series, this indicates that thresholds for comparison with the present level of CO_2 should exist between [0.16, 0.25]x CO_2 in terms of a clear trend component.[7] Furthermore, any of the chosen doses higher than 1x CO_2 also passes a threshold in comparison to 1x CO_2. In addition, doses of 0.25 and 0.5x CO_2 also have seasonally autoregessive terms as well as autoregessive terms of various lag structures, whereas doses higher than 2.0x CO_2 often show a mixture of autoregressive terms and moving average processes. By way of comparison with the interval of [0.79, 2.0]x CO_2, this indicates that more subtle changes are occurring below and above this interval.

The second set of analyses of the NPP of adjacent ratios of CO_2 allows us to further qualify how many thresholds actually exist. As Table 2 shows, the constant terms for any ratio of 1.0 x CO_2 to 2.0 x CO_2 and higher adjacent CO_2 levels are positive, indicating that there are four thresholds in the interval [1.0, 10.0]x CO_2. Furthermore, there is less of a clear threshold to be found between 0.16 x CO_2 and 0.25x CO_2 as compared to the first analysis, however, even here the switch from moving average to various autoregressive processes indicates that the structure of the series is changing. The same can be also found for doses higher than 2.0 x CO_2 to 3.0x CO_2 (see Table 2).[8]

Overall, the results indicate that for an error probability of 0.05, doses larger than 1.0x CO_2 pass NPP thresholds by comparison to 1x CO_2. In addition, by comparison to 1x CO_2, a dose of between 0.16x CO_2 and 0.25x CO_2 constitutes another threshold. More subtle differences in the various structures of the series suggest that there are more complex changes occurring in the series, which fall short of pronounced thresholds.

The validity of the results depends on a series of factors. First, the steps of doses included in the analysis are limited. Smaller intervals of doses will more finely point to where environmental thresholds actually lie. Second, the results should be replicated for other sites in order to replicate the pronounced impact of 3-year climatic cycles found in the various series. Third, the specific site chosen appears to be limited by nitrogen as a nutrient necessary for increased forest growth under high CO_2 levels. While this may reflect reality, it also influences the functional properties of the NPP series. Removing such constraints may

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[7] Interested readers can verify this finding by differencing the series and solving the equations algebraically.

[8] Analyses involving 10.0x CO_2 seem to behave slightly differently compared to those involving smaller doses of CO_2. As estimated parameters are either highly intercorrelated or barely show white noise of residuals, it indicates that perhaps the overall structure of the model is changing or the limits of the model generating the data have been reached. Under any circumstances, 0.16 and 10.0x CO_2 represent *extreme* doses to be included in the

lead to environmental thresholds been found at different levels of atmospheric CO_2 concentration. This also leads to a more important fourth point, namely the adequacy of the model generating the implicit dose-response function. Since models are often best calibrated for conditions of abundant data availability and high data quality, inducing very substantial changes by way of *extremely* varying the dose of one variable (e.g., CO_2) may be quite demanding on the validity of the model. As an alternative to judging the existence of environmental thresholds, actual observations are likely to display only a very reduced range of dose-response relationships. Therefore, the findings based on simulation models necessarily reflect the present state of modeling.

4. Conclusions

The method for detecting thresholds developed in this article shows some distinctive advantages over alternative methods because they provide a less ambiguous foundation for the diagnosis of thresholds. The method for analysis of time-independent responses is based solely on the mathematical properties of the response function and, thus free of any bias. In case of time-dependent response, the proposed approach requires only agreement on statistical significance levels rather than agreement on more complex and often issue-specific normative judgment.[9] Thus, the method for detection of thresholds becomes considerably non-arbitrary. In addition, the same type of statistical analysis can be applied to any data series of environmental data - thus solving the problem of intercomparison across environmental domains. Finally, the ratios analyzed do not have any metric attached, thereby reinforcing the generic nature of this type of analysis which can be extended to applications outside the environmental domain.

The substantive findings have immediate implications for public policy and the analysis of environment and security issues. If the passing of environmental thresholds reflects a change in the state of the environment, then our prototypical results indicate that only a subset of doses qualify as environmental changes (thresholds). Thus, only if the state of the environment changes, any onset of violent conflict may be potentially caused by

analysis.

9 The sensitivity of the substantive findings to the choice of permissible error probabilities is readily computable (from Tables 1 and 2).

environmental degradation. Based on the findings reported in Section 3, we found that for a range of doses, *no* environmental threshold had been passed whereas for other ranges, thresholds had been passed. Depending on which range of the dose is included in a statistical analysis of violent conflict, the results will underestimate (overestimate) the role of environmental factors if the relevant interval of environmental thresholds is included (excluded).

In addition, our diagnosis may have substantive implications for the choice of response strategies and their usefulness. If a change in environmental variable scores was mistaken in representing environmental changes and violent conflict subsequently occurred, decision-makers might emphasize responses which try to limit or remove the environmental problem. Such a strategy might lead to an inefficient use of resources that could conceivably be spent on non-environmental projects. Conversely, a correct detection of a change in the state of the environment might profitably direct decision-makers to invest into strategies to limit or reduce environmental changes. In fact, a finely tuned dose-response function developed on the basis of the method developed further above may assist in targeting investment into environmental remedies.

While the method developed above is generic, its application to a particular domain necessarily reflects the state of knowledge, either based on actual observations or simulated by models. In undertaking our analyses, we assumed that the model output is "true", i.e., the simulated outputs are those to be expected to occur if the actual doses were indeed introduced. As a result of limiting the number of doses to n, we cannot find more than $(n-1)$ thresholds. Increasing the number of doses increases the potential number of thresholds, not necessarily their actual number. Regrettably, simulated extreme doses can rarely be replicated empirically esp. since most researchers and decision-makers would agree that the passing of the thresholds with extremely adverse consequences is to be avoided. To limit erroneous conclusions, we suggest that researchers replicate their findings with a variety of data sources and models that would help to analyze the sensitivity of their conclusions.

In our structured simulation experiment with subsequent statistical analysis, we have compared a set of doses kept constant over long time intervals. This procedure served as an approximation for the comparison of responses to discrete states of environmental doses. By contrast, actual environmental changes occur through more gradual or accelerated changes of the dose and potentially abrupt changes in the environmental response. After all, concentration of atmospheric CO_2 had fluctuated during the earth's history. To mimic better environmental changes over time, future research should introduce more gradual changes of the dose by employing a variety of functional forms for its change. As a result, not only the magnitude of the dose may matter but also the shape of its transitions from one level to another. Detection of environmental thresholds is a useful undertaking that helps to account for environmentally induced violent conflict and to assess the usefulness of investments into environmental remedies. Moreover, it provides warning signs for decision-makers that not any change in an environmental variable is equivalent to a change in the state of the environment.

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Figures and Tables

Figure 1: Absolute and Jump Discontinuity

Figure 2: Local Minimum and Maximum

Figure 3: **Computed NPP for Various Levels of CO_2**

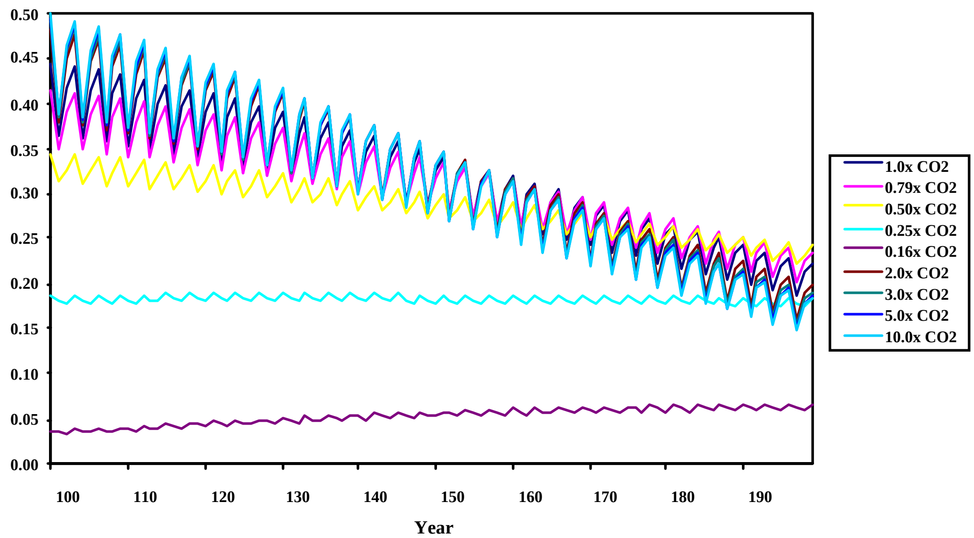
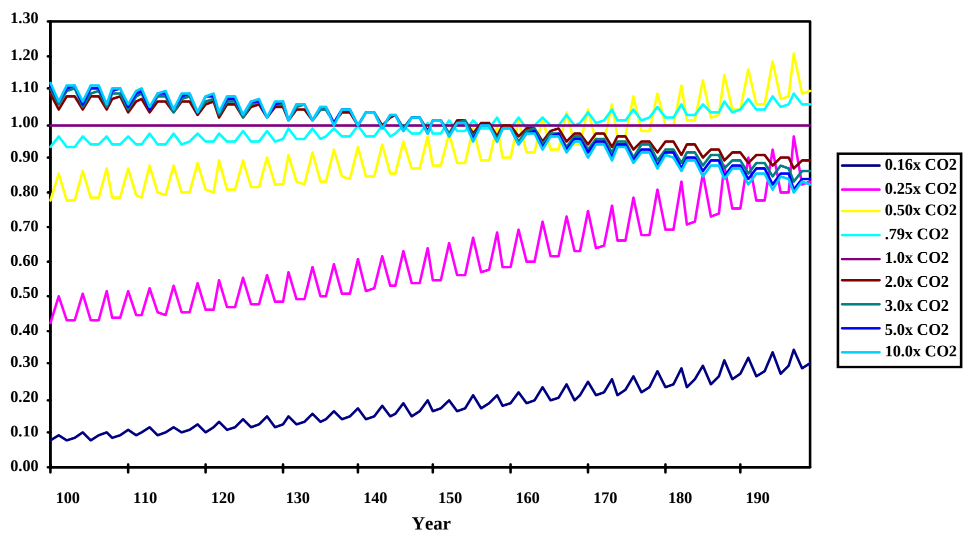
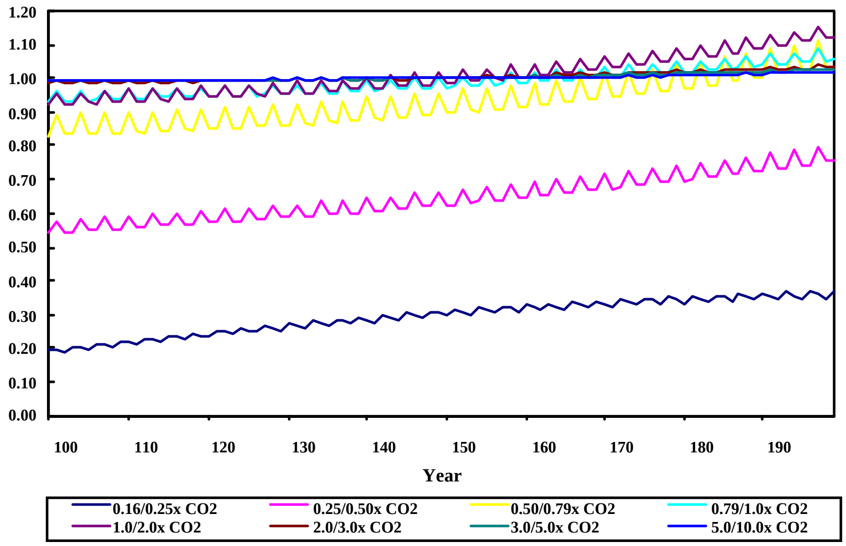


Figure 4: **NPP Ratios Relative to 1.0x CO_2**



<u>Figure 5:</u> **NPP Ratios of Adjacent CO_2 Doses**



<u>Table 1:</u> ARIMA Analysis for NPP Computed as Ratios to 1x CO_2

Level of CO_2	Constant	AR(1)	AR(3)	AR(5)	AR(6)	MA(1)	MA(3)	MA(5)	MA(10)	SAR(3)	Remark
0.16	positive					positive					
0.25	0	negative								see Remark	SAR(3)>0 at p=.07; cases > year 107
0.50	0				positive					positive	
0.79	0										
1.0											reference level
2.0	negative										
3.0	negative	see Remark							negative		AR(1)<0 at p=.07
5.0	negative			negative							
10.0	negative			negative				see Remark			MA(5)<0 at p=.06; coefficients for AR(5) and MA(5) are highly intercorrelated

<u>Notes:</u> N=100 years if not indicated otherwise. Degrees of freedom are lost due to differencing.
All series were differenced once (non-seasonally) and twice seasonally (3-year cycle); all functions were transformed using the natural logarithm. Results are reported for p=0.05 significance levels if not indicated otherwise.
AR(x) refers to a non-seasonal autoregressive term for a lag of "x" years; MA(y) to a non-seasonal moving average for a lag of "y" years; and SAR(z) to a seasonal autoregressive term for a lag of "z" years.

<u>Table 2:</u> ARIMA Analysis for NPP of Adjacent Ratios of CO_2 Levels

Level of CO_2	Constant	AR(1)	AR(3)	AR(5)	AR(6)	MA(1)	MA(3)	MA(5)	MA(10)	SAR(3)	Remark
0.16/0.25	0					negative					
0.25/0.50	0		negative			positive	negative			positive	cases > year 107
0.50/0.79	0				positive					positive	
0.79/1.0	0										same as ratio of 0.79 to 1x CO_2 in Table 1
1.0/2.0	positive										inverse of ratio to 1x to 2x CO_2 in Table 1
2.0/3.0	positive		see Remark				positive			positive	AR(3)<0, not significant
3.0/5.0	positive		negative				positive			positive	
5.0/10.0	positive		see Remark	negative			positive			see Remark	AR(3)<0 at p=.06, SAR(3)>0 at p=.08; borderline for white noise

<u>Notes:</u> N=100 years if not indicated otherwise. Degrees of freedom are lost due to differencing.
All series were differenced once (non-seasonally) and twice seasonally (3-year cycle); all functions were transformed using the natural logarithm. Results are reported for p=0.05 significance levels if not indicated otherwise.
AR(x) refers to a non-seasonal autoregressive term for a lag of “x” years; MA(y) to a non-seasonal moving average for a lag of “y” years; and SAR(z) to a seasonal autoregressive term for a lag of “z” years.