# The effect of climate variation on agro-pastoral production in Africa

Leif Christian Stige*, Jørn Stave*, Kung-Sik Chan†, Lorenzo Ciannelli*, Nathalie Pettorelli*, Michael Glantz‡, Hans R. Herren§¶, and Nils Chr. Stenseth*¶

*Centre for Ecological and Evolutionary Synthesis, Department of Biology, University of Oslo, P.O. Box 1066, Blindern, 0316 Oslo, Norway; †Department of Statistics and Actuarial Science, University of Iowa, 263 Schaeffer Hall, Iowa City, IA 52242; ‡Center for Capacity Building, National Center for Atmospheric Research, P.O. Box 3000, Boulder, CO 80307; and §Millennium Institute, 2200 Wilson Boulevard, Suite 650, Arlington, VA 22201-3357

Contributed by Hans R. Herren, January 4, 2006

**Using national crop and livestock production records from 1961–2003 and satellite-derived data on pasture greenness from 1982–2003 we show that the productivity of crops, livestock, and pastures in Africa is predictably associated with the El Niño Southern Oscillation and the North Atlantic Oscillation. The causal relations of these results are partly understandable through the associations between the atmospheric fluctuations and African rainfall. The range of the explained among-year variation in crop production in Africa as a whole corresponds to the nutritional requirements for ≈20 million people. Results suggest reduced African food production if the global climate changes toward more El Niño-like conditions, as most climate models predict. Maize production in southern Africa is most strongly affected by El Niño events. Management measures include annual changes in crop selection and storage strategies in response to El Niño Southern Oscillation-based and North Atlantic Oscillation-based predictions for the next growing season.**

El Niño Southern Oscillation | North Atlantic Oscillation | Normalized Difference Vegetation Index | food production | nonlinear statistical modelling

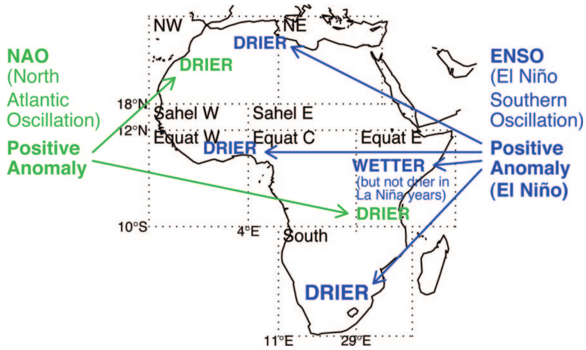


**Fig. 1.** The association between interannual variation in African climate and NAO and ENSO, indices of large-scale climatic variability, as reported in the literature. The representation is a simplification, as e.g., temporal aspects are not considered. To simplify the assessment of the climate impacts (compare Table 1) Africa is divided into regions that display similar agro-pastoral responses (dashed lines). Note that these regions are not necessarily identical to the geographic extents of the reported climate effects.

Global climate change is no longer a hypothesis (1), and we need to better understand its impact on ecosystems and society (2). Africa is particularly vulnerable to climatic variability as its economies are largely based on weather-sensitive agro-pastoral production systems. This vulnerability has been demonstrated by the devastating effects of the various prolonged droughts in the 20th century. To develop effective agro-pastoral management strategies to cope with climatic variability and change, we need detailed knowledge about how different crop and livestock types respond to climatic variation in the different regions of Africa. Although it is the local weather that affects plants and animals, indicators of large-scale climate processes, such as the El Niño Southern Oscillation (ENSO) (3) and the North Atlantic Oscillation (NAO) (4), can often be used to account for ecological processes better than a reliance only on local weather variables, because they reduce complex space and time variability into simple measures (5, 6). Another interest in the use of such climate proxies is that their states can be predicted several months ahead (7, 8) and that their possible long-term change is an important component of future climate projection scenarios (1).

Primarily ENSO, large-scale air-sea variability in the equatorial Pacific (3), but also the NAO, North Atlantic north-south alternation in atmospheric mass (4), is linked with climatic variability in Africa as a result of atmospheric teleconnections (9–12) (Fig. 1). For example, the risk of drought in southern Africa increases by 120% in El Niño years (warm ENSO anomalies) (13). More generally, warm ENSO anomalies lead to rainfall deficits in southern, western, and northeastern Africa and rainfall surpluses in eastern Africa, whereas cold ENSO anomalies have roughly the opposite effects (9–11). Positive NAO anomalies (steep North Atlantic air pressure gradient) lead to rainfall deficits in northwestern and southeastern Africa, whereas negative NAO anomalies lead to rainfall surpluses in the same areas (4, 12, 14). Effects of ENSO (15–17) and NAO (ref. 18 but see ref. 19) on interannual variation in primary production in different regions of Africa have been shown, using the satellite-derived Normalized Difference Vegetation Index (NDVI) (20, 21) to measure vegetation greenness. Effects on agricultural primary production have also been demonstrated, but to our knowledge only at local scales. For example, Cane *et al.* (22) showed that >60% of the variance in Zimbabwean maize yield could be accounted for by an index of ENSO and that accurate predictions of yield could be made with lead times of up to 1 year. Because of the predictable association between ENSO and African climate, ENSO information is being used with other information to forecast and mitigate climatic impacts on water supplies, food production, and human health in southern and eastern Africa (23–25). We believe that such use of ENSO and NAO information could be even more fruitful if the link between these indices and food production is empirically assessed at large spatial scales.

Here we take an all-African perspective, aiming to quantify the effects of ENSO and NAO on agro-pastoral production. How do these effects differ geographically, and how do they differ among crop or animal types? How much food do the effects correspond to in terms of the number of people who could be fed

Conflict of interest statement: No conflicts declared.

Abbreviations: ENSO, El Niño Southern Oscillation; NAO, North Atlantic Oscillation; NDVI, Normalized Difference Vegetation Index.

¶To whom correspondence may be addressed. E-mail: hansrherren@mac.com or n.c.stenseth@bio.uio.no.

© 2006 by The National Academy of Sciences of the USA

on above- or below-average production? For this purpose we used the unique FAOSTAT data set (http://faostat.fao.org) from the Food and Agriculture Organization of the United Nations. These data show the actual agro-pastoral production in different countries each year for >40 years. Our results are therefore directly interpretable in terms of total amounts of food produced in each country. For crops we analyzed interannual variability in yield (harvested production per cultivated area), and for livestock we analyzed interannual variability in slaughter weights. Because slaughter weights are also influenced by human management decisions, we also analyzed variability in pasture productivity measured by NDVI in three parts of Africa (Mali, Kenya, and Botswana).

## Results and Discussion

We find strong associations between year-to-year variability in ENSO and yields of maize, sorghum, millet, and groundnuts (Fig. 2 and see Figs. 3–12, which are published as supporting information on the PNAS web site, for plots for all countries with available data). This association is strongest for southern Africa, where productivity is expected to drop by 20–50% in extreme El Niño years. Note that for sorghum, millet, and groundnuts the response is nonlinear, as the ENSO effect is only apparent when the ENSO index surpasses certain thresholds, either an upper threshold (El Niño years) or a lower threshold (La Niña years). The western regions of the continent show similar but weaker responses for millet and maize, whereas sorghum and groundnut yields in northwest Africa appear to increase during El Niño years. In contrast, rice shows a weaker and geographically more uniform response to ENSO, whereas cassava and wheat show no response at all. The weaker response for these crops may be partly caused by more frequent use of irrigation. However, rice shows a rather strong response to variability in the NAO, particularly in the northern and central parts of the continent (where ENSO generally has relatively low effect). In addition, variability in the NAO is associated with variability in the yields of groundnuts and cassava.

The climate impacts on the total production of different crops in different regions of Africa are summarized in Table 1. The effects we observe are strong, particularly so for southern Africa, and particularly so for maize, where the difference in production between the extreme warm and cold ENSO phases corresponds to what is required to feed close to 15 million people in 1 year (see Table 2, which is published as supporting information on the PNAS web site). These effects concern southern Africa especially, where maize is the most important food crop, and Africa generally, where southern Africa is the most important maize-producing area. For Africa as a whole, the effect of variation in ENSO on maize corresponds to what is required to feed a total of close to 20 million people in a year. The corresponding figures for sorghum, millet, rice, and groundnuts are ≈2 million to 3 million people. When it comes to the impacts of NAO variability, the corresponding figure for sorghum is ≈5 million people, for rice almost 3 million people, and for cassava almost 2 million people. Although these figures are highly theoretical, they do give an impression of the order of magnitude of the effects. Any management measures that could mitigate some of the negative climate effects would help a large number of people.

When it comes to the effects on pastures and livestock, we find that slaughter weights of goats are positively associated with the previous-year NAO index in the western parts of Africa. For cattle and sheep no response to either ENSO or NAO is found. Using NDVI data we find that pasture productivity is negatively associated with the ENSO index in Botswana and negatively with the NAO index in Kenya (long growing season only; Fig. 2), probably reflecting direct effects of precipitation variability. There are also indications of delayed ENSO effects in Kenya and a slight ENSO effect in Mali, but the latter depends on a single La Niña year with high NDVI (Fig. 13, which is published as supporting information on the PNAS web site). The finding of climatic effects on pasture productivity but not on livestock in some regions could

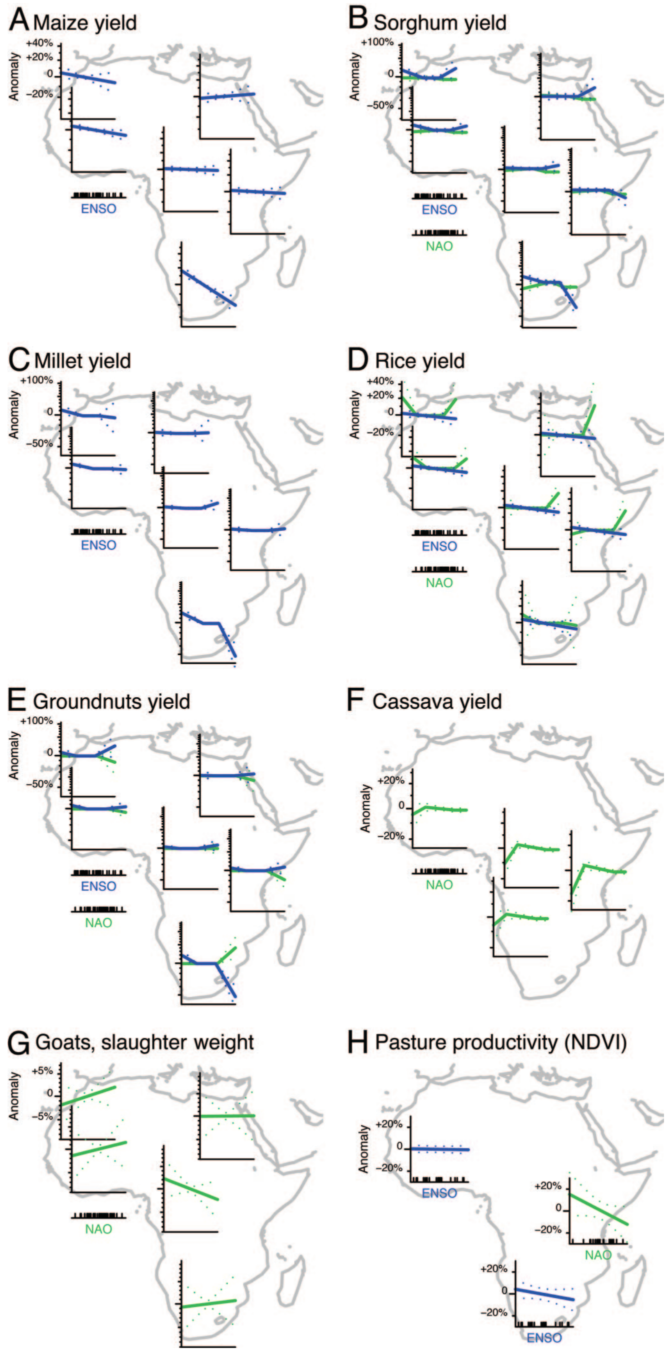


**Fig. 2.** Predicted yearly anomalies in agro-pastoral productivity in Africa in response to ENSO (blue lines) and NAO (green lines). ENSO and NAO are indices of large-scale climatic variability. *A–G* are based on FAOSTAT data from 1961–2003 and show predictions ±2 SE on logarithmic scales for representative countries for which data exist (see Figs. 3–12 for all countries). *H* shows climate effects (±2 SE, linear scale) on the NDVI, a satellite-derived measure of primary production, for pastoral regions in Mali, Kenya, and Botswana for 1981–2003. The NDVI response for the Kenyan long growing season is shown (the short-season response is included in Fig. 13). The tick marks on the ENSO and NAO scales show the locations of the observations of these variables.

**Table 1. Climate effects on crop production**

| Region | Year* | Maize | Sorghum | Millet | Rice | Groundnuts | Cassava |
|---|---|---|---|---|---|---|---|
| Amount required to feed 1 million people† | | 228 | 224 | 255 | 300 | 191 | 752 |
| NW | Normal | 130 | 68 | 9 | 80 | 49 | 0 |
| | High ENSO | −5 | +3 | +0 | −2 | +5 | — |
| | Low ENSO | +5 | +9 | +1 | +2 | +3 | — |
| | High NAO | +0 | −2 | +0 | +2 | −3 | — |
| | Low NAO | +0 | −1 | +0 | +4 | +0 | — |
| NE | Normal | 6,327 | 975 | 7 | 6,400 | 224 | 0 |
| | High ENSO | +117 | +68 | +0 | −145 | +4 | — |
| | Low ENSO | −96 | +1 | +0 | +124 | +1 | — |
| | High NAO | +0 | −51 | +0 | +532 | −11 | — |
| | Low NAO | +0 | +23 | +0 | +11 | +0 | — |
| Sahel W | Normal | 1,531 | 2,443 | 2,675 | 1,213 | 1,088 | 205 |
| | High ENSO | −55 | +57 | −9 | −34 | −7 | +0 |
| | Low ENSO | +47 | +217 | +236 | +30 | +73 | +0 |
| | High NAO | +0 | −114 | +0 | +27 | −6 | −1 |
| | Low NAO | +0 | −57 | +0 | +49 | +0 | +2 |
| Sahel E | Normal | 185 | 5,706 | 3,015 | 211 | 1,903 | 403 |
| | High ENSO | +0 | +228 | +53 | −6 | +65 | +0 |
| | Low ENSO | +0 | +7 | +97 | +5 | +36 | +0 |
| | High NAO | +0 | −348 | +0 | +10 | −67 | −6 |
| | Low NAO | +0 | +1 | +0 | +4 | +0 | −6 |
| Equat. W | Normal | 3,379 | 749 | 358 | 3,092 | 1,122 | 19,206 |
| | High ENSO | −114 | +8 | +1 | −96 | −36 | +0 |
| | Low ENSO | +99 | +52 | +29 | +82 | +68 | +0 |
| | High NAO | +0 | −39 | +0 | +27 | +10 | −170 |
| | Low NAO | +0 | −23 | +0 | +91 | +0 | +55 |
| Equat. C. | Normal | 7,337 | 8,038 | 5,602 | 5,796 | 3,187 | 55,005 |
| | High ENSO | −202 | +247 | +67 | −172 | +25 | +0 |
| | Low ENSO | +173 | +335 | +305 | +148 | +120 | +0 |
| | High NAO | +0 | −454 | +0 | +170 | +2 | −706 |
| | Low NAO | +0 | −182 | +0 | +130 | +0 | −359 |
| Equat. E | Normal | 8,780 | 2,898 | 1,192 | 835 | 279 | 12,596 |
| | High ENSO | −101 | −108 | +25 | −27 | +9 | +0 |
| | Low ENSO | +89 | +3 | +32 | +23 | +13 | +0 |
| | High NAO | +0 | −216 | +0 | +34 | −18 | −229 |
| | Low NAO | +0 | −35 | +0 | −2 | +0 | −217 |
| South | Normal | 14,893 | 1,001 | 316 | 280 | 706 | 17,409 |
| | High ENSO | −1,741 | −164 | −37 | −10 | −115 | +0 |
| | Low ENSO | +1,643 | +85 | +42 | +9 | +75 | +0 |
| | High NAO | +0 | −94 | +0 | +7 | +35 | −280 |
| | Low NAO | +0 | −67 | +0 | +5 | +0 | −128 |
| Total | Normal | 42,561 | 21,878 | 13,175 | 17,908 | 8,558 | 104,824 |
| | High ENSO | −2,101 | +339 | +100 | −492 | −49 | +0 |
| | Low ENSO | +1,961 | +710 | +742 | +422 | +389 | +0 |
| | High NAO | +0 | −1,318 | +0 | +810 | −58 | −1,392 |
| | Low NAO | +0 | −340 | +0 | +291 | +0 | −654 |

Expected total crop production ($10^3$ metric tons) in different parts of Africa during normal years and anomalies during extreme ENSO or NAO years. The numbers are based on country-specific estimates, using information on cultivated area, time-averaged yield, and geographic-specific climate effects, and are summed across the countries in each region (as defined in Fig. 1).

*Climatically normal or extreme years of magnitudes as expected to occur every 20 years, as estimated by the 5% and 95% percentiles of the ENSO or NAO indices 1961–2003 [ENSO: −0.89 (La Niña) and 1.13 (El Niño), NAO: −3.53 and 3.91].

†The amount needed to feed 1 million people for 1 year at 2,000 calories per person per day.

be caused by management interventions (e.g., supplemental feeding, pastoralist mobility) or a general excess of pastures in these areas, but more detailed data would be needed to determine this issue.

Our results imply that African food production may be severely reduced if the global climate changes toward more El Niño-like conditions, as most climate models predict (1). This effect is largely caused by lower total maize yields. It should, however, be added that this projection of the results does not take into account climate-related changes in the amount of land suitable for farming or direct effects of increased $CO_2$ on crops (26). Negative effects could be mitigated by improved technology, including increased use of irrigation, and changes in land use, including the planting of alternative crops. As to the latter strategy, our results indicate which crops might be more favorable in which part of Africa under an El Niño-like regime.

Because ENSO, and to some extent NAO, can be forecast (7, 8), our analysis suggests a prognostic measure. First, our results demonstrate that early predictions can be made on how climate will affect the total production of different crops in the different regions of Africa. Hence, governments and nongovernmental organizations can be better prepared for potential shortages and advised where to organize strategic staple food reserves. Second, farmers can be advised ahead of extreme climatic years to plant different crops. For example, cassava and sorghum have wide soil and climatic adaptability ranges, including tolerance to drought, and they are well known to farmers throughout the region. Our analyses point toward some caution in the case of sorghum, because in the most extreme El Niño years in southern Africa (drought years) sorghum yields are equally strongly affected as, for example, maize. Planting at least a part of the available land with cassava would then create a safety net (27). However, in other parts of Africa, maize and sorghum yields show opposite responses to El Niño events (see Tables 1 and 2). Our results thus suggest that switching from maize to sorghum in these regions ahead of El Niño years may be advantageous.

Some caution is needed before downscaling our results to local conditions. For example, crops may respond differently when grown together with other crops. Mixed cropping is a widespread practice among small-scale farmers in Africa, which buffers food production against the effects of climatic fluctuations. Further, our analysis looks at large-scale patterns of the climatic effects, and thus averages out differences between regions within countries and microclimatic effects. Our results show the general patterns of the climatic effects, and, not the least, the effects on the total amounts of food produced.

A recent G8 meeting (www.g8.gov.uk) pointed out that "[a]ll countries need further access to information and to develop the scientific capacity that will allow their governments to integrate climate, environmental, health, economic and social factors into development planning and resilience strategies. We note that Africa's data deficiencies are greatest and warrant immediate attention." Our study demonstrates that much valuable data do indeed already exist, data which, if properly analyzed, may put us into a stronger position for dealing with an increasingly more variable climate.

## Methods

**Data.** Agricultural productivity data (annual mean yields or slaughter weights) for continental Africa 1961–2003 was obtained from the United Nations FAOSTAT database (http://faostat.fao.org). Reportedly constant productivity for 3 years or more in a country was considered spurious and such data series were not used, nor were data for countries with <10 years of data. Data of productivity of maize, sorghum, millet, wheat, rice, cassava, groundnuts, cattle, sheep, and goats were used. The numbers of countries included in the final data set for each crop or livestock type were 42, 38, 35, 29, 37, 32, 41, 27, 14, and 11, respectively. The numbers of year-country combinations were 1,737, 1,551, 1,372, 1,099, 1,481, 1,226, 1,604, 866, 357, and 289, respectively.

Primary production of pastoral regions of Mali, Kenya, and Botswana for 1982–2003 was measured by NDVI (20, 21) (see *Supporting Text*, which is published as supporting information on the PNAS web site). We here used the data collected by the National Oceanic and Atmospheric Administration satellites and processed by the Global Inventory Monitoring and Modeling Studies group (28). Average growing season NDVI was used to estimate annual pasture productivity. The two growing seasons of Kenya (long and short) were treated separately. See Fig. 13 for geographic locations and growing season periods.

The ENSO index was derived from monthly (February, March, and April) equatorial Pacific sea surface temperature anomalies in the Nino-3.4 region (3). We also considered ENSO indices based on anomalies in the northern fall, winter, or summer, but these generally showed weaker relationships with agro-pastoral production (but see Fig. 13). We used Hurrell's winter NAO index based on the difference of normalized sea level pressure between Ponta Delgada, Azores and Stykkisholmur/Reykjavik, Iceland (4). ENSO data were provided by the National Oceanic and Atmospheric Administration Climate Prediction Center, Camp Springs, MD (www.cpc.ncep.noaa.gov/data/indices), and NAO data were provided by the Climate Analysis Section, National Center for Atmospheric Research, Boulder, CO (www.cgd.ucar.edu/cas/jhurrell/indices.html). The ENSO and NAO indices are not correlated in the study period (Pearson's coefficient of correlation = 0.03). See Stenseth *et al.* (5) for a review on the use of ENSO and NAO in ecological studies.

**Statistical Analyses.** To account for long-term trends in agricultural productivity caused by technical innovations, changes in land use, agro-political changes, etc., we fitted generalized additive models (GAMs) (29) for each country with log-transformed yield or slaughter weight as response and the year effect modeled by a smooth term with maximally 4 knots (3 df). The residuals from these models, i.e., the detrended productivity, were used as response in the subsequent analyses. We used the GAM implementation of the "mgcv" library of R (30).

To investigate the possible association between large-scale climatic fluctuations and (detrended) agro-pastoral productivity, we fitted generalized additive models for each crop or livestock type. All countries were analyzed in one model. Geographic differences in climatic effects were modeled by interactions between linear functions of ENSO or NAO and smooth functions of the latitude and longitude of each country. The effects of climate were allowed to change abruptly across one or two thresholds in the climatic variable, the threshold values being estimated from the data (31, 32). For any given locality the model was piecewise linear, which has several advantages compared with other nonlinear model formulations (32). For fixed thresholds the full model can be written as:

$$
\begin{aligned}
RP_{ij} = k_0 + s_0(long_i, lat_i) \\
&+ (k_1 + s_1(long_i, lat_i))(ENSO_j - e_1)I(ENSO_j \leq e_1) \\
&+ (k_2 + s_2(long_i, lat_i))(ENSO_j - e_1)I(ENSO_j > e_1) \\
&+ (k_3 + s_3(long_i, lat_i))(ENSO_j - e_2)I(ENSO_j > e_2) \\
&+ (k_4 + s_4(long_i, lat_i))(NAO_j - n_1)I(NAO_j \leq n_1) \\
&+ (k_5 + s_5(long_i, lat_i))(NAO_j - n_1)I(NAO_j > n_1) \\
&+ (k_6 + s_6(long_i, lat_i))(NAO_j - n_2)I(NAO_j > n_2) \\
&+ \varepsilon_{ij},
\end{aligned}
$$

where $RP_{ij}$ is residual productivity for the given crop or livestock type in country $i$ in year $j$; $e_1$ and $e_2$ are threshold values of the ENSO index; $n_1$ and $n_2$ are threshold values of the NAO index; $long_i$ and $lat_i$ are the longitude and latitude of the country; $k_0$–$k_6$ are constants; $s_0$–$s_6$ are smooth functions with maximally eight dimensions; the operator $I$ designates indicator variables (1,0); and $\varepsilon_{ij}$ is a noise term of zero mean and finite variance. For example, when the ENSO index is between $e_1$ and $e_2$ the estimated slope of the ENSO effect in country $i$ equals $k_2 + s_2(long_i, lat_i)$. The formulation ensured the climate effects to be continuous across the thresholds. The constants are included because the smooth terms are constrained to sum to zero for model identification purposes (33). We also considered models with one threshold or no threshold for either climate variable, as well as models with climatic effects in only some regimes of the threshold variable (e.g., ENSO effects only when ENSO is above $e_2$ or below $e_1$, but not between $e_1$ and $e_2$) and models without climate effects. Leave-1-year-out cross validations were used to find the best model structure for each crop or livestock type. See also *Supporting Text* and Table 3, which is published as supporting information on the PNAS web site.

The pasture productivity data were analyzed separately for each country (and for Kenya, growing season) by using generalized additive models of NDVI in response to smooth terms of ENSO and NAO (maximally 3 knots). The model structure was primarily chosen based on the generalized cross-validation criterion (30, 32), but a term was not included in the model if it only led to a small improvement of this criterion, its estimated degrees of freedom was close to 1, and its plotted confidence band included zero everywhere (30, 32).

Analyses with indicator variables for the most extreme values confirmed that outliers have little influence on the conclusions of the study (*Supporting Text*).

Comments provided by reviewers Fritz Schulthess and Esa Ranta helped sharpen this article. This work has primarily been funded through core funding to the Centre for Ecological and Evolutionary Synthesis received from the University of Oslo. However, without the funding received from the Global Environment Facility, World Bank and Norwegian Agency for Development Cooperation to the Management of Indigenous Vegetation for the Rehabilitation of Degraded Rangelands in the Arid Zone of Africa (www.ivp-rcu.org/index.htm) the work reported in this article would never have materialized.

1. Intergovernmental Panel on Climate Change (2001) *Climate Change 2001: The Scientific Basis* (Cambridge Univ. Press, Cambridge, U.K.).
2. Stenseth, N. C., Mysterud, A., Ottersen, G., Hurrell, J. W., Chan, K.-S. & Lima, M. (2002) *Science* **297,** 1292–1296.
3. Trenberth, K. E. (1997) *Bull. Am. Meteorol. Soc.* **78,** 2771–2777.
4. Hurrell, J. W. (1995) *Science* **269,** 676–679.
5. Stenseth, N. C., Ottersen, G., Hurrell, J. W., Mysterud, A., Lima, M., Chan, K.-S., Yoccoz, N. G. & Ådlandsvik, B. (2003) *Proc. R. Soc. London Ser. B* **270,** 2087–2096.
6. Hallett, T. B., Coulson, T., Pilkington, J. G., Clutton-Brock, T. H., Pemberton, J. M. & Grenfell, B. T. (2004) *Nature* **430,** 71–75.
7. Chen, D., Cane, M. A., Kaplan, A., Zebiak, S. E. & Huang, D. (2004) *Nature* **428,** 733–736.
8. Rodwell, M. J. (2003) in *The North Atlantic Oscillation: Climatic Significance and Environmental Impact*, eds. Hurrell, J. W., Kushnir, Y., Ottersen, G. & Visbeck, M. (Am. Geophys. Union, Washington, DC), Geophysical Monograph 134, pp. 173–192.
9. Nicholson, S. E. & Selato, J. C. (2000) *Int. J. Climatol.* **20,** 1761–1776.
10. Camberlin, P., Janicot, S. & Poccard, I. (2001) *Int. J. Climatol.* **21,** 973–1005.
11. Paeth, H. & Friederichs, P. (2004) *Clim. Dyn.* **23,** 815–837.
12. McHugh, M. J. & Rogers, J. C. (2001) *J. Clim.* **14,** 3631–3642.
13. Thomson, M. C., Abayomi, K., Barnston, A. G., Levy, M. & Dilley, M. (2003) *Lancet* **361,** 437–438.
14. Lamb, P. J. & Peppler, R. A. (1987) *Bull. Am. Meteorol. Soc.* **68,** 1218–1225.
15. Anyamba, A. & Eastman, J. R. (1996) *Int. J. Remote Sensing* **17,** 2533–2548.
16. Anyamba, A., Tucker, C. J. & Mahoney, R. (2002) *J. Clim.* **15,** 3096–3103.
17. Ingram, J. C. & Dawson, T. P. (2005) *Philos. Trans. R. Soc. A* **363,** 55–59.
18. Oba, G., Post, E. & Stenseth, N. C. (2001) *Global Change Biol.* **7,** 241–246.
19. Wang, G. (2003) *Global Change Biol.* **9,** 493–499.
20. Tucker, C. J., Dregne, H. E. & Newcomb, W. W. (1991) *Science* **253,** 299–301.
21. Pettorelli, N., Vik, J. O., Mysterud, A., Gaillard, J.-M., Tucker, C. J. & Stenseth, N. C. (2005) *Trends Ecol. Evol.* **20,** 503–510.
22. Cane, M. A., Eshel, G. & Buckland, R. W. (1994) *Nature* **370,** 204–205.
23. Dilley, M. (2000) *Clim. Change* **45,** 63–73.
24. Glantz, M. H. (2001) *Once Burned, Twice Shy? Lessons Learned from the 1997–98 El Niño* (United Nations University, Tokyo).
25. Patt, A., Suarez, P. & Gwata, C. (2005) *Proc. Natl. Acad. Sci. USA* **102,** 12623–12628.
26. Intergovernmental Panel on Climate Change (2001) *Climate Change 2001: Impacts, Adaptation, and Vulnerability* (Cambridge Univ. Press, Cambridge, U.K.).
27. Kamukondiwa, W. (1996) *Clim. Res.* **6,** 153–155.
28. Tucker, C. J., Pinzon, J. E., Brown, M. E., Slayback, D., Pak, E. W., Mahoney, R., Vermote, E. & El Saleous, N. (2006) *Int. J. Remote Sensing*, in press.
29. Hastie, T. J. & Tibshirani, R. J. (1990) *Generalized Additive Models* (Chapman and Hall, London).
30. Wood, S. N. (2001) *R News* **1/2,** 20–25.
31. Ciannelli, L., Chan, K.-S., Bailey, K. M. & Stenseth, N. C. (2004) *Ecology* **85,** 3418–3427.
32. Stenseth, N. C., Chan, K.-S., Tavecchia, G., Coulson, T., Mysterud, A., Clutton-Brock, T. & Grenfell, B. (2004) *Proc. R. Soc. London Ser. B* **271,** 1985–1993.
33. Wood, S. N. (2004) *J. Am. Stat. Assoc.* **99,** 673–686.