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Human Ecology, Resilience, and Security in 2030

Howard Passell, Len Malczynski, Marissa Reno, Daniel Villa

Prepared by
Sandia National Laboratories
Albuquerque, New Mexico 87185 and Livermore, California 94550

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Howard Passell, Len Malczynski, Marissa Reno, Daniel Villa
Sandia National Laboratories
P.O. Box 5800
Albuquerque, New Mexico 87185-0734

Abstract

Resilience is a quality that allows human systems to rebound from shocks, such as droughts or famines, floods, conflict events, and others. Human resilience is tightly coupled to human ecology, including population dynamics, resource availability, and resource consumption. The Human Resilience Index (HRI) and Modeling (HRIM) Project provides a set of tools that help explore the links among human ecological conditions, human resilience, and conflict. The HRIM allows users to simulate future scenarios and mitigation strategies. Historic calculations using the HRI show numerous times and places where declining HRI values have corresponded to instability and conflict, supporting the hypothesis that poor human ecological conditions can contribute to conflict. Seven indicators are used to calculate the HRI: population growth rate, population density, caloric intake per capita, renewable fresh water per capita, arable land per capita, median age, and population health (including infant and child mortality and life expectancy). The HRIM provides a set of tools for evaluating alternative mitigation strategies to help improve human ecological conditions, increase resilience to shocks, and reduce the threat of instability and conflict.

Acknowledgments

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Nomenclature

Title	Definition
D.R.	Democratic Republic (Congo)
FSI	Failed States Index
HRI	Human Resilience Index
HRIM	Human Resilience Index and Modeling
MID	Militarized Interstate Dispute
UCDP	Uppsala Conflict Program Armed Conflict Dataset
UN	United Nations

1. Introduction

Three very important, long-term, robust, and slow-to-change trajectories are shaping the future of human systems on Earth. These three trajectories are increasing population growth, increasing consumption of resources, and decreasing availability of resources. These are all characteristics of human ecology, which is the study of human populations and their interactions with each other and with the Earth's physical and biological environments. All three trajectories have important impacts on human social, political, and economic systems, and on both human security and national security.

Resilience is a quality that allows human systems to rebound from shocks, such as droughts or famines, floods, human migration or conflict events, and others. Our hypotheses are that human ecological conditions and human resilience are tightly coupled, that human systems with poor human ecological conditions will be less resilient to shocks, and in the event of those shocks they will be more prone to collapse into instability and conflict. This work helps test these hypotheses.

The Human Resilience Index and Modeling work (HRIM) is currently applied to 154 countries using United Nations (UN) data from 1961-2008, and using seven indicators (population growth, population density, median age, per capita caloric intake, per capita freshwater, per capita arable land, and population health, which includes infant and child mortality and life expectancy). The HRIM applies two modeling methods to bracket and test model results. The modeling projects Human Resilience Index (HRI) values for countries into the future.

This work provides a set of analytical and quantitative tools that help explore the links among human ecological conditions, human resilience, conflict, and peace, and allows users to simulate tradeoffs and consequences associated with different future development and mitigation scenarios.

2. Methods and Results

The HRI assumes that poor human ecological conditions, such as hurricanes or floods, droughts, refugee migrations, economic failures, or ethnic clashes, degrade resilience to shocks in human systems. In a human system with strong resilience, shocks can be absorbed and the system can return relatively quickly toward an average value. In a human system with poor resilience, shocks may cause wide oscillations in system behavior that lead to even more extreme conditions, which in turn may lead to severe forms of instability, violence, or conflict. The HRI focuses on the risk of various forms of instability, violence, or conflict associated with poor human ecological conditions, but not with economic, political, or social conditions. Future versions of the HRI will attempt to integrate those parameters.

The HRI ranks countries according to their human ecological condition and resilience to shocks associated with that condition. The HRI calculates values from historic data from 154 countries for the historical period of 1961-2008, and then projects values from 2009-2030 using both a non-dynamic and dynamic modeling method.

Human ecological conditions are simulated in the HRI with seven indicators and three sub-indicators (Figure 1). The UN World Population Prospects (2010 Revision,

(http://esa.un.org/unpd/wpp/index.htm) and the UN Environment Programme Environmental Data Explorer (http://geodata.grid.unep.ch/) provided the data. The overall availability of data was an important constraint in the selection of the indicators and sub-indicators.

We experimented with numerous sets of indicators before settling on the one described in Fig. 1, which we concluded is parsimonious while covering the some of the most important indicators of the human ecological condition. Population growth rate and density capture population dynamics. Median age helps describe the age structure of the population as a whole, which has been shown to contribute to different measures of stability.[1] Per capita values for caloric intake, renewable freshwater, and arable land capture important resource limitations on the human population. Population health, made up of lifespan, infant mortality and child mortality, provide a snapshot of human health.

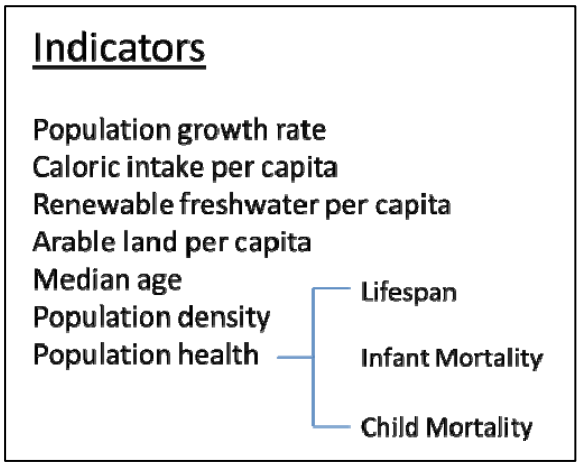


Figure 1. Indicators and Sub-indicators

Energy is one crucial component of a human ecological system that is not included in this set of indicators because we considered it to be so closely interconnected with economy. Our effort was to isolate the effect of the human ecological condition on stability and conflict, and so we excluded indicators that touched too strongly on other sectors. Also, we felt that many other indices have been developed to evaluate multi-sectoral issues, and we chose to focus our efforts on an index aimed at only human ecology and resilience. Future efforts in this work should include energy, and linkages to effects from other sectors such as economy, ethnicity, religion, and politics.

2.1. Calculation of HRI

The HRI is calculated using Eq. 1. Simply, the HRI is calculated for any country and any year by taking the indicator value (I_i), subtracting the average indicator value from all countries for that year ($\overline{I_i}$), and dividing by the standard deviation ($\overline{\overline{I_i}}$) of the indicator values from all the countries for that year. This 'standardizes' indicator values and puts them all in roughly the same numeric range. All indicators are equally weighted (w_i), although the sign (+ or -) varies. Indicators that are judged to improve the human ecological condition (caloric intake, renewable fresh water, arable land, median age, and lifespan) have a positive sign, and those judged to impair the human ecological condition have a negative sign. The sum ($\sum$) of all the standardized indicator values provides the HRI value for the country in a given year. More detail on the calculation and testing of the HRI is shown in *Appendix A.*

[1] Cincotta, R., 2008-2009. Half a chance: youth bulges and transitions to liberal democracy. Environmental Change and Security Program Report, Woodrow Wilson Center, Washington, DC.

$$HRI = \sum_i w_i \frac{I_i - \overline{I_i}}{\overline{\overline{I_i}}} \qquad \text{Eq. 1}$$

Figure 2 shows the HRI values from 1961-2008 for the 15 countries at highest risk of failure on account of their poor human ecological conditions and poor resilience. For comparison, Figure 3 shows the 15 countries at lowest risk. Three of the countries at highest risk show pronounced downward oscillations of the HRI corresponding to periods of conflict: Somalia with its invasion of Ethiopia in 1977, Malawi with food riots in 1988, and Afghanistan with the fall of Kabul and civil war in 1992 and 1993. Notably, the HRI for the 15 highest risk countries is decreasing over time, and the HRI for the 15 lowest risk countries is increasing.

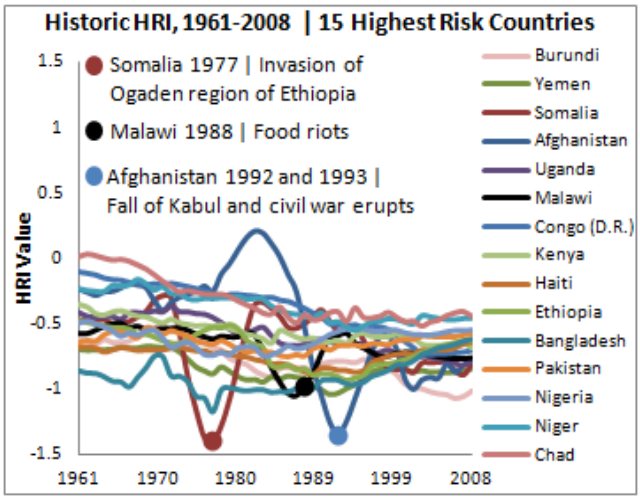


Figure 2. 15 Highest Risk Countries

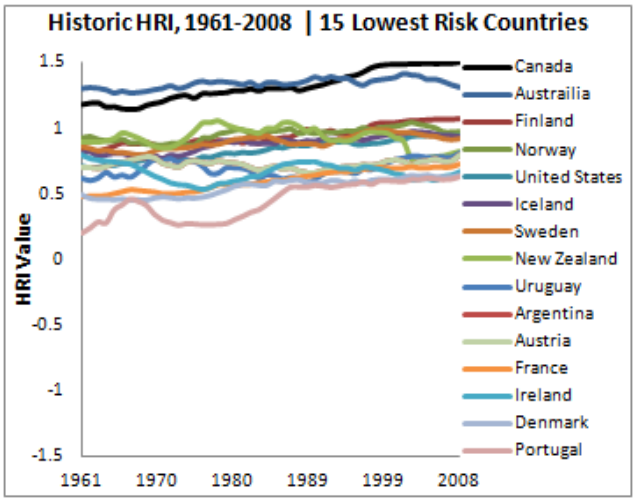


Figure 3. 15 Lowest Risk Countries

Numerous correspondences between declining HRI and conflicts occur in countries other than the 15 at highest risk and are shown in *Appendix B.* The HRI does not capture all conflict events in any of the countries analyzed. This may be because some conflicts are more closely related to ethnic, religious, political, or economic issues than to human ecological conditions. Also, some declines in the HRI do not correspond to conflict events. These may be examples where other conditions play greater roles in human events than human ecological conditions.

In Figure 2 above, the declining HRI scores for Somalia, Malawi, and Afghanistan reflect high human population growth driven largely by human migration events, and compounded by high underlying fertility rates in conjunction with falling per capita caloric intake.

These results help provide a quantitative metric for how sudden increases in population growth along with food shortages may be reliable indicators for potential conflict or instability. The historical values of all indicators used in the HRI calculation for the 15 highest-risk countries during 1961-2008, and other results, are shown in the *Supplemental Information* attachment at the end of the report.

2.2. Application of Failed State Index Filter

The results shown in Figure 2 above are not the lowest-scoring countries in the HRI for 2008. The first column in Table 1 shows the 30 lowest-scoring countries in the HRI for 2008. These are defined as the countries with the poorest human ecological conditions, but not necessarily the countries at greatest risk of failure. The United Arab Emirates has the overall lowest score primarily because of its low values for renewable freshwater and arable land, and its high population growth rate, but it is not widely viewed as a country at risk of failure. Singapore has the 10th lowest score primarily because of its high population density and a lack of fresh water and arable land, but it is an example of how good governance and a healthy economy that is not directly reliant on native natural resources can balance the human ecological conditions described by the HRI.

Table 1. FSI applied as a filter to HRI results

Rank	2008 HRI	2008 FSI
1	United Arab Emirates	Somalia
2	Burundi	Sudan
3	Rwanda	Zimbabwe
4	Yemen	Chad
5	Comoros	Iraq
6	Somalia	Congo (D. R.)
7	Afghanistan	Afghanistan
8	Uganda	Cote d'Ivoire
9	Malawi	Pakistan
10	Singapore	Central African Rep.
11	Congo (D. R.)	Guinea
12	Kenya	Bangladesh
13	Maldives	Myanmar
14	Haiti	Haiti
15	Kuwait	North Korea
16	Ethiopia	Ethiopia
17	Bangladesh	Uganda
18	Pakistan	Lebanon
19	Tanzania	Nigeria
20	Liberia	Sri Lanka
21	Gambia	Yemen
22	Nigeria	Niger
23	Zambia	Nepal
24	Angola	Burundi
25	Jordan	Timor-Leste
26	Benin	Kenya
27	Mozambique	Congo (Republic)
28	Burkina Faso	Uzbekistan
29	Niger	Malawi
30	Chad	Solomon Islands

Table 1 shows how the HRI results in 2008 are compared with the Failed States Index[2] (FSI) 2008 results as a means of filtering out states that have poor human ecologies but which are not at imminent risk of failure. The remaining countries, highlighted in blue, are those countries common to both the HRI and the FSI, which we define as those at greatest risk of failure due to poor human ecology.

The first column in Table 2 shows the same 15 countries from Table 1 (which are the same 15 highest-risk countries in Fig. 2). The second column in Table 2 shows the same countries from column 1, but with the non-dynamic modeling applied to them. The non-dynamic modeling uses Eq. 1 with UN projections to 2030 for population growth and density, infant and child mortality, and life expectancy. Per capita renewable freshwater and arable land vary as a function of population growth. Caloric intake, which varied widely over the historic period, was projected forward using a 10-year running average.

[2] Fund for Peace, Washington, DC. http://www.fundforpeace.org/global/?q=fsi

Table 2. HRI results across modeling methods

Rank	2008 Historic	2030 Non Dynamic	2030 Dynamic Pre-FSI Filter	2030 Dynamic Post-FSI Filter
1	Burundi	Somalia	Somalia	Somalia
2	Yemen	Malawi	Burundi	Burundi
3	Somalia	Afghanistan	Rwanda	Yemen
4	Afghanistan	Burundi	Singapore	Uganda
5	Uganda	Uganda	Yemen	Afghanistan
6	Malawi	Yemen	Comoros	Malawi
7	Congo, D.R.	Kenya	Uganda	Congo, D.R.
8	Kenya	Congo, D.R.	Afghanistan	Kenya
9	Haiti	Nigeria	Malawi	Nigeria
10	Ethiopia	Niger	Congo, D.R.	Niger
11	Bangladesh	Haiti	Kenya	Pakistan
12	Pakistan	Chad	Nigeria	Chad
13	Nigeria	Pakistan	Zambia	Haiti
14	Niger	Ethiopia	Jordan	Ethiopia
15	Chad	Bangladesh	Tanzania	Bangladesh

The third column in Table 2 shows the 15 lowest scoring countries in 2030 from the dynamic model, but before the FSI filter is applied. The fourth column shows the results of the dynamic model in 2030, but filters out countries not included in the 2008 FSI.

We expect some correlation between the FSI and the HRI, since the FSI includes some environmental parameters similar to those in the HRI. If no correlation between HRI and FSI exists, then the probability that 15 countries out of 30 correspond is 0.0016%, as calculated in Eq. 2. The expected number of corresponding countries is 5 or 6 with no correlation. This shows that poor ecological conditions are correlated strongly (though not perfectly) to the state failure described by the FSI.

$$p(15) = \frac{\binom{30}{15}\binom{154-30}{30-15}}{\binom{154}{30}} \qquad \text{Eq. 2}$$

In the dynamic model, each indicator is connected to other indicators, often through intermediate variables, so that a change in one indicator ripples through the model making impacts on other indicators, and eventually looping back. Methods used in the dynamic modeling are described in detail in *Appendix C*.

3. Confidence in the Modeling

Confidence in the validity and usefulness of the model as a representation of real dynamics in the world is achieved in various ways. Figures 4 and 5 compare the results of the dynamic model with results from the historic model. The correspondence in slope, variability, and overall shape of the distribution lends confidence in the ability of the dynamic model to project dynamics into the future. Figure 4 shows the historic HRI values for the highest risk countries from 1961-2008

(same graph as in Figure 2) and Figure 5 shows the dynamically modeled HRI values for the same countries over the same period.

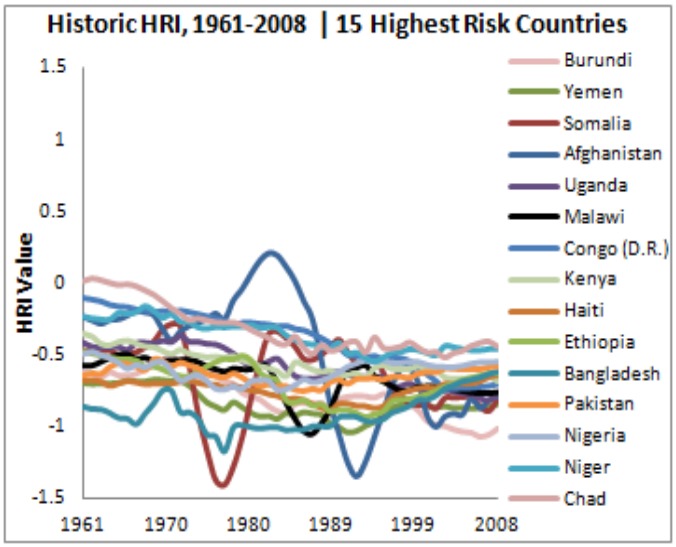


Figure 4. 15 Highest Risk Countries (Historic Model)

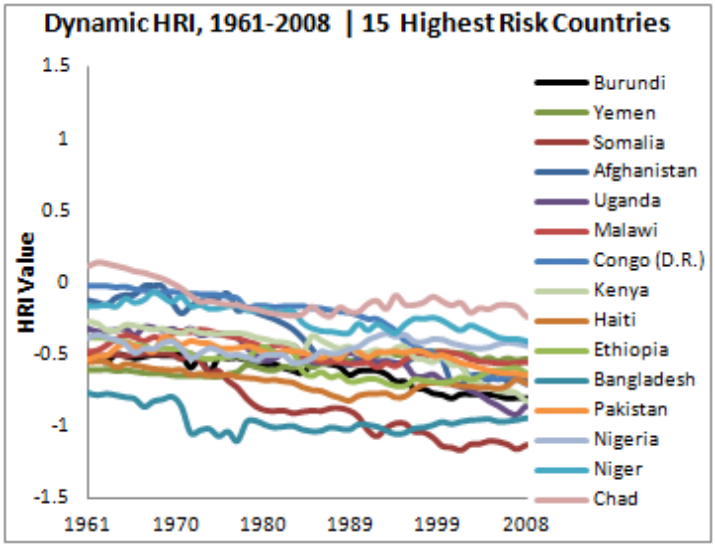


Figure 5. 15 Highest Risk Countries (Dynamic Model)

The dynamic model does not capture dramatic oscillations, such as those in Somalia in 1977, Malawi in 1988, and Afghanistan in 1992-93, because those events are driven by 'exogenous' events — events that occur outside the boundaries of those applied to the model. In those cases, for example, high migration rates from one country to another were critical to driving the HRI down, but migration from one country to the other is not a variable in the current model.

Another factor that lends confidence to the modeling is the internal and external consistency evident across various modeling results. The first kind of external consistency is that the model results make sense. The highest risk countries are widely viewed by observers and analysts as unstable countries prone to conflict, and the lowest risk countries are widely viewed as stable ones. Analysis of model results, in fact, show that the year to year variability in the HRI for the lowest scoring countries is two times the variability in the highest scoring countries (see *Appendix D*). In other words, the countries identified by the HRIM as being less stable and more prone to oscillations are in fact less stable in a statistical sense. Another factor lending confidence in the modeling is the internal consistency shown by the occasional correspondence between non-dynamic and dynamic model results, an example of which will be seen more clearly in the Somalia scenario described below. Inconsistent results across different analyses could be a warning sign, but the consistency offers assurance. (Inconsistencies between non-dynamic and dynamic results and a brief discussion of them can be found in the *Supplemental Information* attachment at the end of the report.)

Confidence in the overall HRIM is gained through analysis of the HRI results as compared to the Uppsala Conflict Program Armed Conflict Dataset (UCDP; Figure 6)[3] version 4-2012 created by Gleditsch, et al. (2002) and maintained by Themnér & Wallensteen (2012). This analysis shows strong evidence that a decreasing HRI score indicates an increased probability of the

[3] http://www.pcr.uu.se/research/UCDP/

development of a major government-based conflict, either between countries or due to internal strife. Figure 6 shows that the probability of armed conflict in countries from the UCDP database drops as the HRI increases. The black line includes all countries common to the UCDP and the HRI analyses, and the blue line shows common countries but excludes countries that were conflict free. More detailed explanation of this analysis can be found in *Appendix E*.

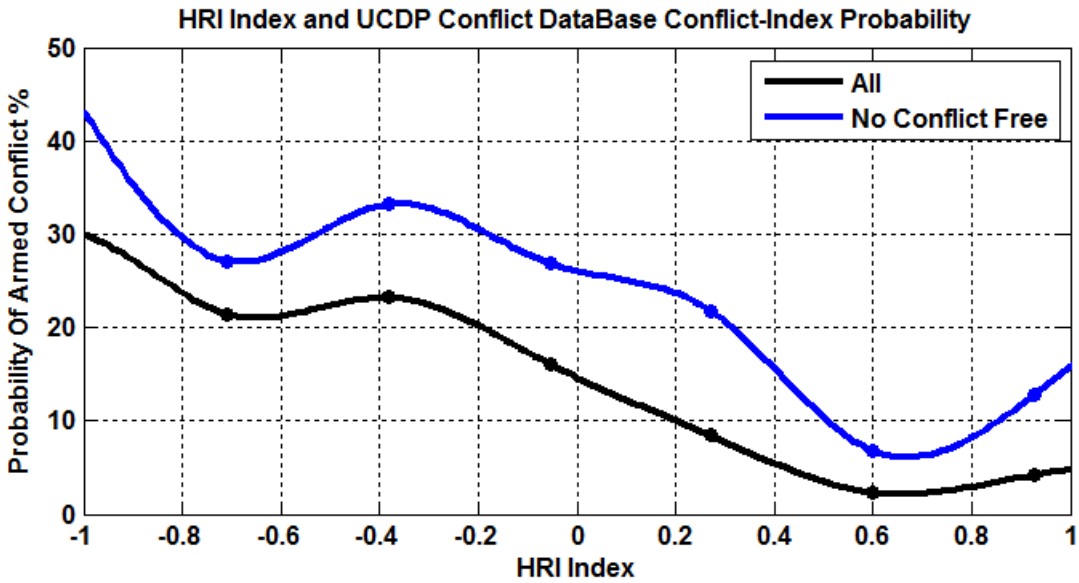


Figure 6. HRI Index and UCDP Conflict Database Conflict-Index Probability

Any examples of consistency in the model may simply be the predictable results of all our modeling decisions, and may be expected to emerge just as they have. None of these examples can be interpreted as proof that the modeling is accurately reflecting the real systems. Analysis with a second conflict database did not return interesting results. We believe, however, that there is sufficient evidence that the modeling is useful for exploring and better understanding the dynamics in real systems. This will permit policy makers and the public to experiment with different strategies and gain insight into the behavior of the systems

4. Somalia Scenario

The HRI can be used to experiment with current and future mitigation strategies that might improve regional conditions and help relieve the pressures leading to instability and conflict. As a case study we used the HRI to test several future scenarios in Somalia (Figure 7), which appears as the lowest scoring country in 2030 in dynamic results (Table 2). The green line in Figure 7 shows the results for Somalia from the dynamic model for the years 2009-2030. How could Somalia's position be improved? The red and black lines in Figure 7 respectively, show the results from the non-dynamic model and the dynamic model for simulating a doubling in 2013 of caloric intake, freshwater availability, and arable land. The correspondence between the results from the non-dynamic and dynamic modeling is an example of the internal consistency in the modeling that lends confidence in it.

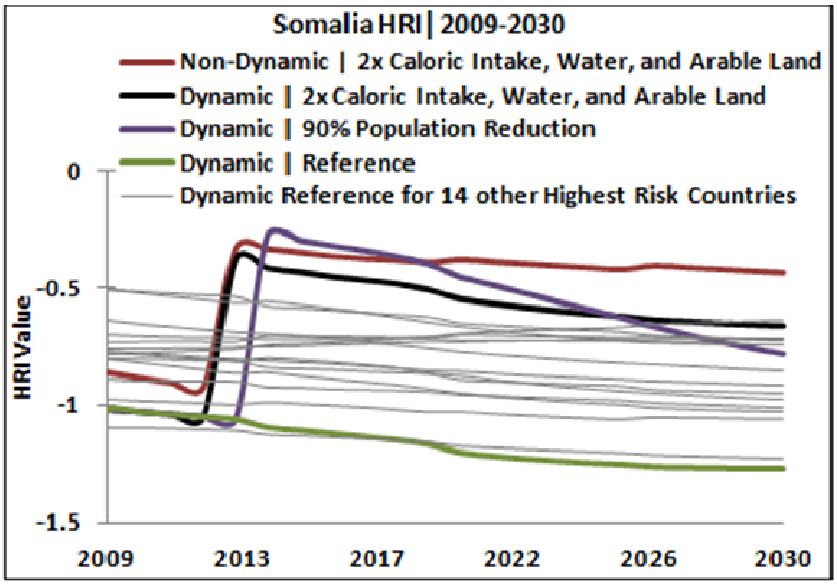


Figure 7. Somalia HRI (2009-2030)

Suddenly doubling the availability of these resources causes the HRI for Somalia to leap. It declines again through the rest of the simulation because of high population growth rates, but it ends in 2030 in a position slightly above the other lowest scoring 14 countries (shown in grey). The purple line shows how approximately the same result could be achieved by reducing population, instead of increasing resource availability. A 90% reduction in population is required. This causes the HRI to leap, and then high population growth rates cause the HRI to decline again through 2030. The gray lines represent the results of the dynamic model for the other 14 highest risk countries.

These simulated strategies – doubling resources or reducing population by 90% – are unrealistic in the sense that there is no apparent way they could be achieved in such short times. The severity of these strategies suggests that Somalia may be a country in which human population and resource consumption have exceeded regional ecological constraints. This simulation suggests quantitatively what the boundary conditions for Somalia's carrying capacity[4] might be. More work must be done to better understand these dynamics.

5. Discussion

The HRIM provides quantitative assessment of the increasing threat of risk associated with human population growth, resource consumption, and resource scarcity. It provides an environment in which users can experiment with different future scenarios including shocks to human ecological systems (drought, famine, etc.) and potential mitigation strategies. The modeling provides a quantitative assessment of potential carrying capacities in countries and regions and the measures that might be taken to prevent or remedy poor conditions. The HRIM provides a set of tools for evaluating alternative mitigation strategies to help improve human ecological conditions and increase resilience to shocks, such as acute food or water shortages,

[4] In ecology, carrying capacity is the maximum population size that an environment can sustain indefinitely, given the available environment's natural resources.

human migration events, conflict events, etc., thereby, reducing the threat of instability and conflict. Overall, the HRIM is a useful framework for considering the sources of instability, conflict, and peace, in and among nations.

Any importance that might reside in this work is not in the ability to rank the highest risk countries, which are already widely assumed to be at risk, but in the development of a model that sufficiently captures dynamics associated with human ecological conditions, resilience, and security. The confidence gained in the model, as described above, suggests that it can be useful for further analysis of those dynamics.

One value of the effort lies in the use of the model by policy analysis or policy making institutions for better evaluating the sources, interdependencies, and trajectories of regional instability and insecurity. More or less real time analysis could help policy makers anticipate dangerous oscillations as they are developing, and allow more time and opportunity for response and mitigation. This kind of real time analysis would require more real time data availability on indicators, and/or different sets of indicators.

Another value of this work is its use among regional stakeholder groups for better understanding regional dynamics, evaluating potential tradeoffs among different future strategies, and for development of long term development strategies aimed at reducing the risk of future instability and conflict. One useful application of this work might be made through a collaborative, stakeholder-driven modeling approach, in which regional stakeholders are engaged at the beginning of the data gathering and modeling process, and then are involved throughout model development and analysis. By being involved from beginning to end the stakeholders will better understand model development, strengths and weaknesses of the data and the modeling, and data gaps, as well as a better understanding of regional dynamics and tradeoffs between different future strategies. By being involved in the modeling and analysis from the beginning, stakeholders better understand the model and so are more able and likely to use it. The collaborative, stakeholder driven approach can also include regional scientists and technicians in data gathering and model development as a way of building modeling and analysis capacity in the region. Ideally, this capacity building can allow regional scientists and technicians to carry on modeling activities into the future and to apply modeling skills to other problems.

A-Appendix: Calculating the Human Resilience Index

Daniel Villa

The human resilience index (HRI) is designed as a ranking of how seven ecological and population based indicators compare among the world's countries. Its seven indicators are population health, median age, population density, population growth rate, caloric intake per capita, arable land per capita, and renewable fresh water per capita. The health indicator is composed of life expectancy, child mortality, and infant mortality data. Each indicator is measured over a set of countries through time. The data for each indicator undergoes two operations in order to make adding the indicators together a fair operation. First, the data are transformed to bring their statistical distribution close to a normal distribution. Second, the average and standard deviation of the data is used to make each indicator have similar significance.

In the first step, a single parameter power transformation is used [1,2]. The power parameter, λ, is optimized to make each indicator as close to a normal distribution as possible. Given the UN data for the set of indicators $i \in \{population\ health, median\ age, \ldots\}$ over the a set of 154 countries used in this study, $j \in \{Afghanistan, Albania\ \ldots\}$, and the time interval $t \in \{1961, 1962, \ldots, 2008\}$[5], the power transform can be written as follows.

$$I'_{i,j,t} = \begin{cases} \dfrac{\left(I_{i,j,t} - s_i\right)^{\lambda_i} - 1}{\lambda_i \left(G_i\left(I_{i,1\ldots m,1\ldots n} - s_i\right)\right)^{\lambda_i - 1}} & \lambda_i \neq 0 \\ G_i\left(I_{i,1\ldots m,1\ldots n} - s_i\right) LN\left(I_{i,j,t} - s_i\right) & \lambda_i = 0 \end{cases}$$

Where $I_{i,j,t}$ is the original indicator data set; λ_i is the order of the power transformation which for this study has been confined to the interval $-2 \leq \lambda \leq 2$; $I'_{i,j,t}$ is the transformed data; s_i is a shift parameter which is used to shift data if any negative data points are present but is equal to zero otherwise; and G_i represents the geometric mean[6] of the mn data points obtained by cycling through $j = 1 \ldots m$ countries and $t = 1 \ldots n$ years.

$$G_i\left(I_{i,1\ldots m,1\ldots n}\right) = \sqrt[mn]{\prod_{j=1}^{m} \prod_{t=1}^{n} I_{i,j,t}}$$

[5] These sets have a specific order which is replaced by 1,2,… instead of always listing the actual names.

[6] The expression in the main text is the classical definition of the geometric mean. It quickly becomes impossible to calculate accurately using double precision calculations. Taking the logarithm of the expression, rearranging, and applying the natural exponent to both sides produces the following alternate form which calculates accurate values for the HRI data:

$$G_i\left(I_{i,1\ldots m,1\ldots n}\right) = e^{\frac{1}{mn} \sum_{j=1}^{m} \sum_{t=1}^{n} LN\left(I_{i,j,t}\right)}$$

The parameter λ_i can be given k values over its interval and the skew, $S_{i,k}$ and kurtosis $K_{i,k}$ calculated for each value of $\lambda_{i,k}$.[7] The Jarques-Bera test statistic [3,4], which is designed to indicate deviation from a normal distribution, can then be used as an objective function whose minimum is the transformation for λ_i which is closest to being normal.

$$J_{i,k} = \frac{mn}{6}\left({S_{i,k}}^2 + \frac{1}{4}\left(K_{i,k} - 3\right)^2\right)$$

Figure A-1 shows the optimization results and Figure A-2 shows the effects the transformation has on

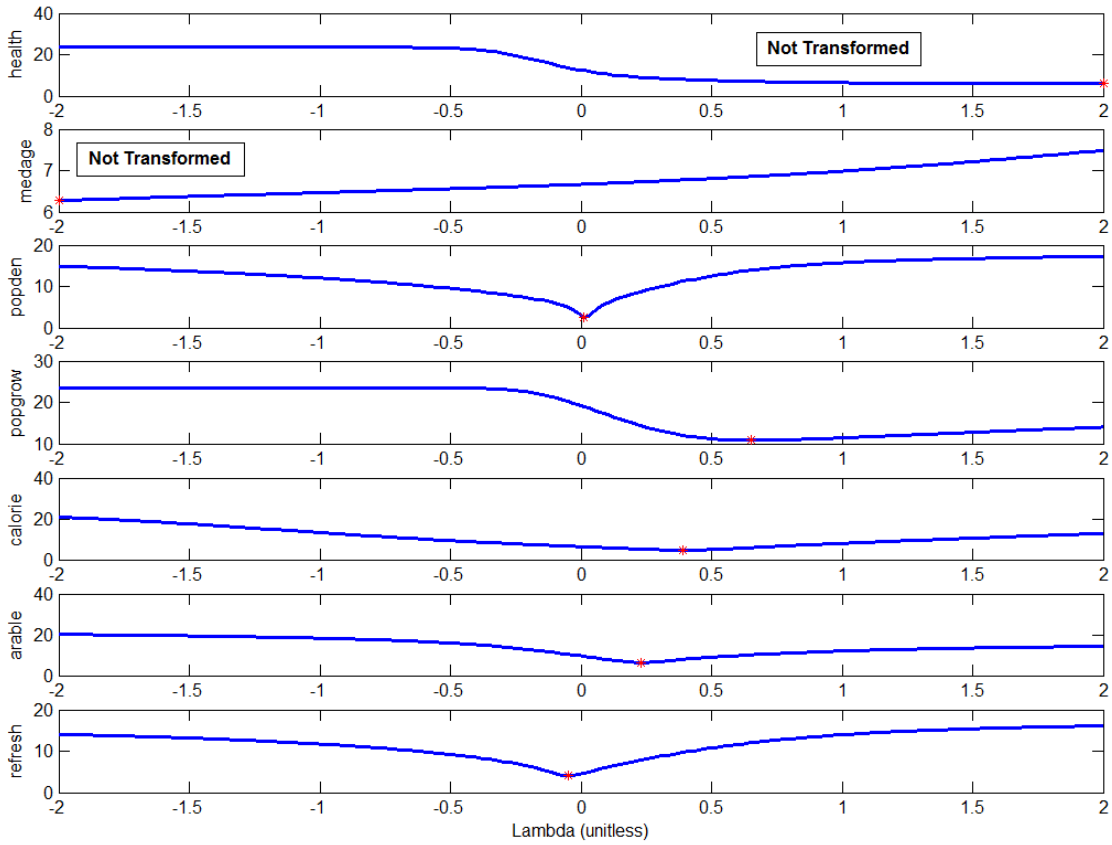


Figure A-1. Minimization of the logarithm of the Jarques-Bera test statistic. The health indicator and median age were not transformed because the results were not very sensitive to transformation.

[7] Skew and Kurtosis are the third and fourth standardized moments of a random variable. The better known average and standard deviation are the first and second moments. Skew provides a measure of how asymmetric a set of data is. Kurtosis provides a measure of how sharply peaked the distribution is. Skew is equal to zero and Kurtosis is equal to 3 (depending on how Kurtosis is defined) for a normal distribution.

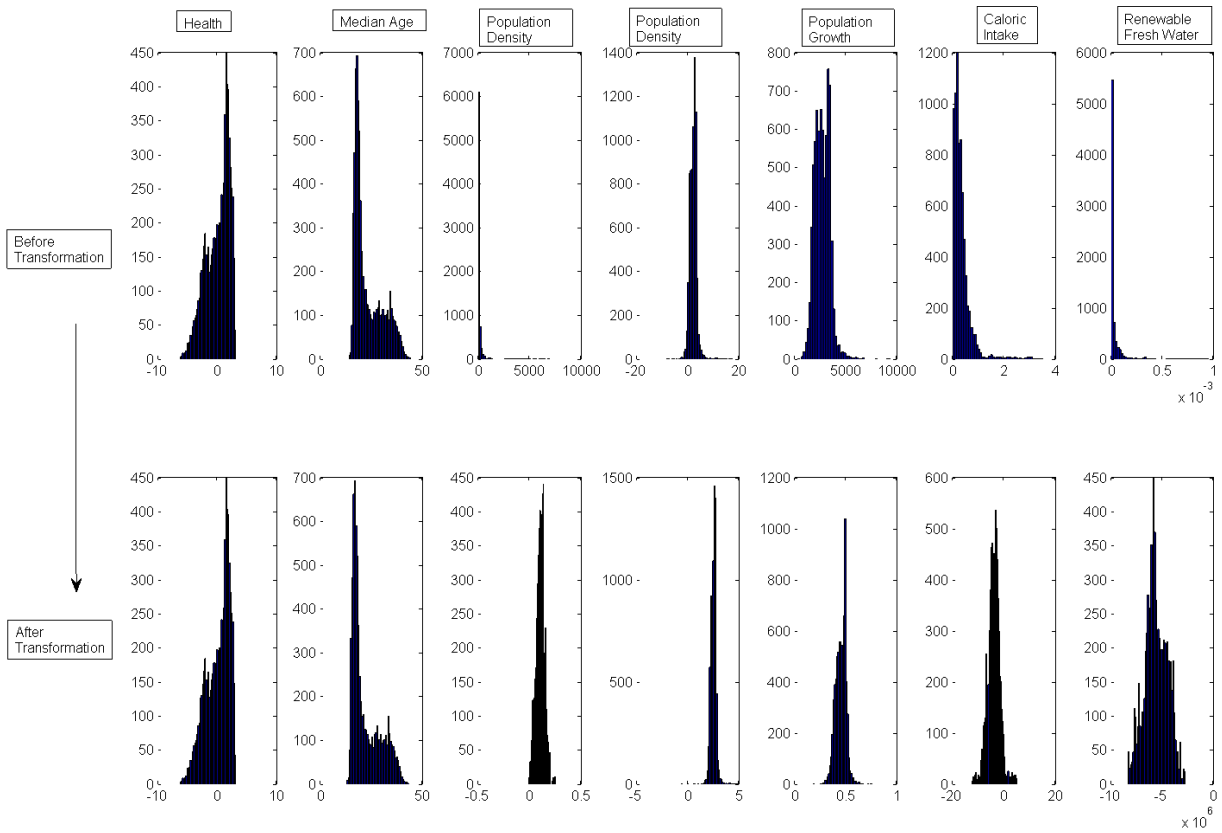


Figure A-2. Indicator distributions before and after transformation

Figure A-2 shows data distributions. The health and median age indicators were not transformed because the sensitivity to the transform was not significant. Both of these distributions are clearly double peaked and do not respond well to the transforms being applied. They are accepted as-is since their deviation from being normal is not nearly as drastic as population density, caloric intake, and renewable fresh water. Alternates to the median age and health indicator were investigated but they are not as desirable since they are less well known. Figure A-3 gives a clear view of why the transformation is needed. On the right hand side a box plot shows that the renewable fresh water, arable land, and population density data all have significant outliers and skew which are orders of magnitude larger than the 75% boundaries of the data. This creates the problem that these outliers make the estimated normal distribution very poor. For example, renewable fresh water is an important resource which has a couple countries which are up to ten times the standard deviation from the mean water amount. As seen in Figure A-4 this causes countries which have nearly zero water in comparison to other countries to only get penalized a very small amount for their low water levels whereas the countries with large amounts of water are given too much credit for abundant water. The skew in the data needs to be removed to make the comparison fair.

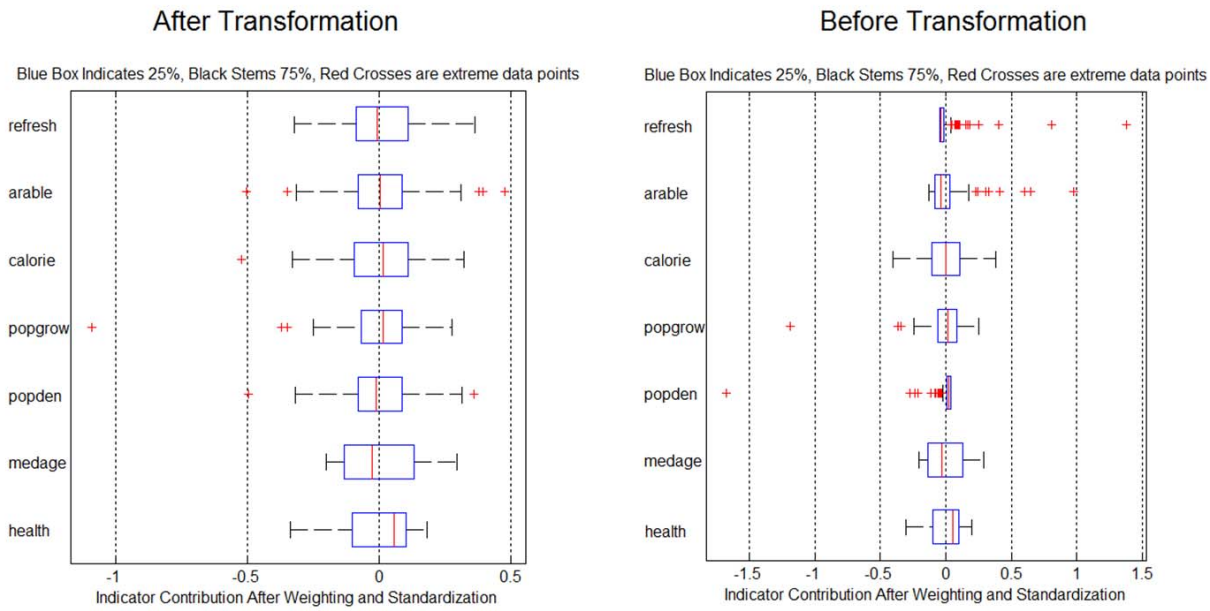


Figure A-3. Illustration showing how transformation has made the contribution of each indicator much more uniform when weighted with equal importance. The ideal goal is for each box to have the same bounds.

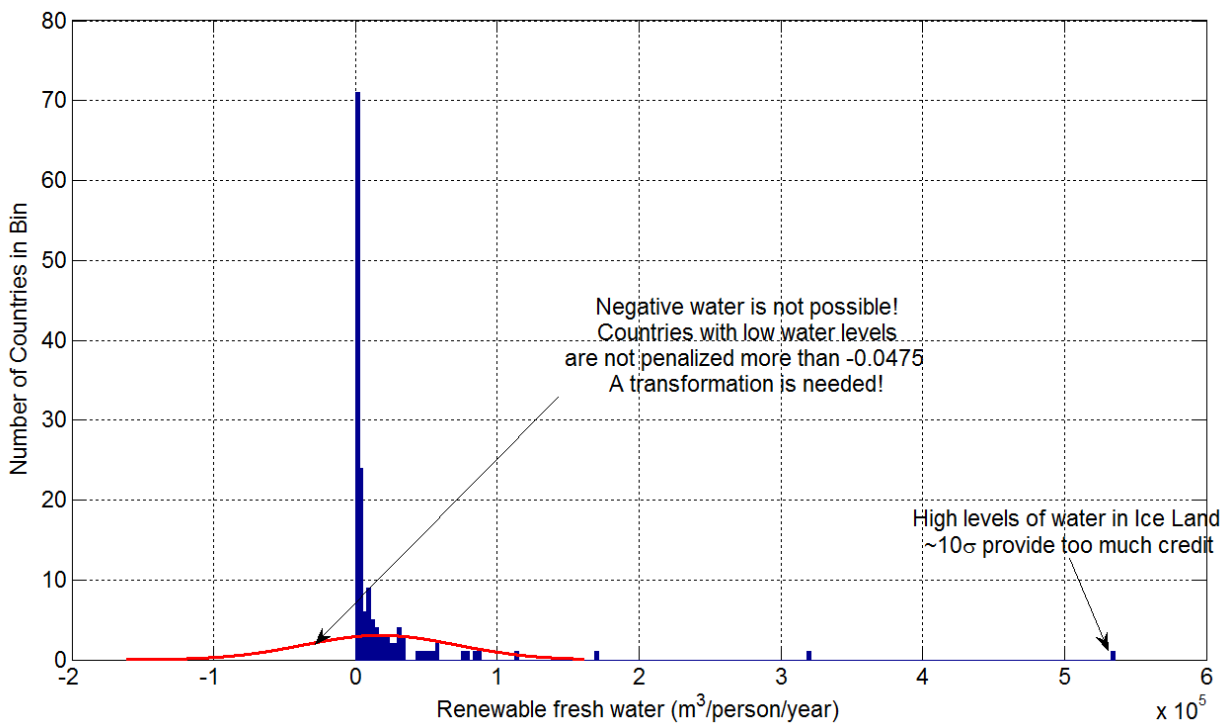


Figure A-4. Renewable fresh water data showing why transformations are needed

The "health" indicator is unique among the indicators because it is composed of three additional data sets. It is a linear combination of life expectancy, infant mortality, and child mortality data which is calculated before transformation. These three measures were combined as an attempt to cover a broader range of health issues.

$$I_{health,j,t} = \frac{I_{lifeexp,j,t} - \bar{I}_{lifeexp}}{\bar{\bar{I}}_{lifeexp}} - \frac{1}{2}\left(\frac{I_{InfantMort,j,t} - \bar{I}_{InfantMort}}{\bar{\bar{I}}_{InfantMort}} + \frac{I_{ChildMort,j,t} - \bar{I}_{ChildMort}}{\bar{\bar{I}}_{ChildMort}}\right)$$

$\bar{I}$ represents the mean and $\bar{\bar{I}}$ the standard deviation of the data over time and countries. The sum of the mortality data is multiplied by ½ because both data sets are assumed to be very similar to each other in their effects.

Once the health indicator has been calculated and transformations applied, the second step involves normalizing the transformed data to have an average of zero and standard deviation of one. The average and standard deviation are taken over the set of countries for this calculation but not over the times.

$$I''_{i,j,t} = \frac{1}{7}\frac{I'_{i,j,t} - \bar{I}'_{i\,t}}{\bar{\bar{I}}'_{i\,t}}$$

$I''_{i,j,t}$ is the contribution of each indicator to the HRI. The factor of one-seventh is added to scale the HRI to have a standard deviation of one. The HRI is the sum of $I''_{i,j,t}$ over the indicators.

$$HRI_{j,t} = \sum_i f_i I''_{i,j,t}$$

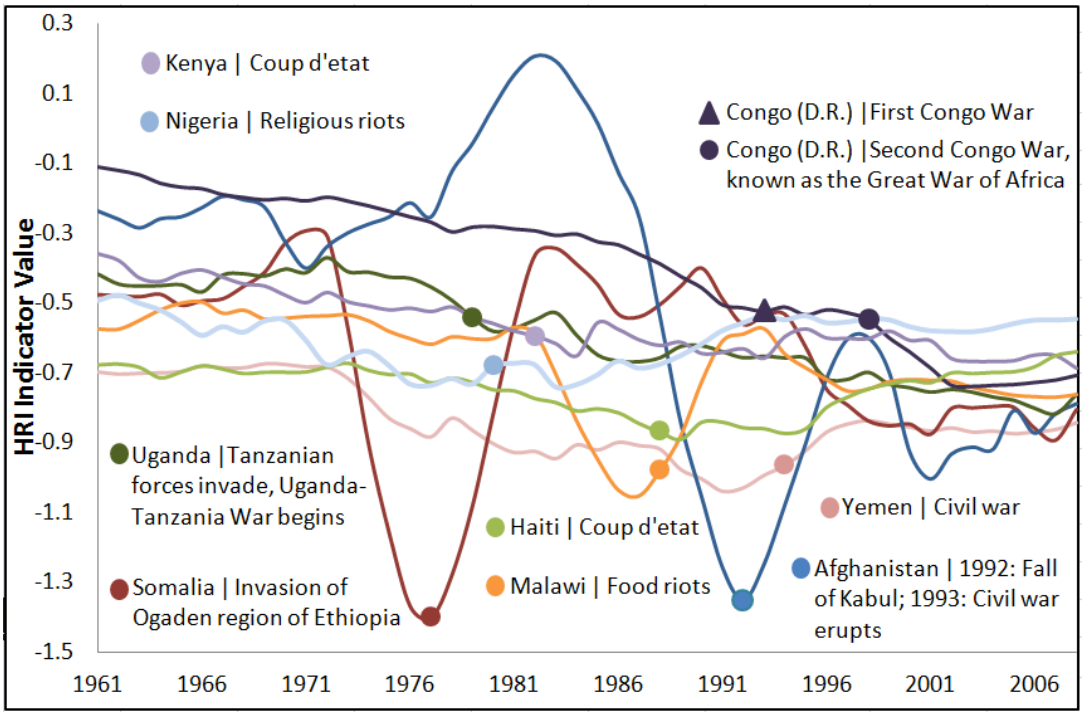
The factor f_i is either positive or negative one depending on whether a high value is desirable ($f_i = 1$) or if a high value is not desirable ($f_i = -1$) . All of the indicators except population growth and population density have f_i equal to one.

References

1. http://en.wikipedia.org/wiki/Power_transform
2. Box, George E. P.; Cox, D. R. (1964). "An analysis of transformations". *Journal of the Royal Statistical Society, Series B* **26** (2): 211-252.
3. http://en.wikipedia.org/wiki/Jarque%E2%80%93Bera_test
4. Jarque, Carlos M.; Bera, Anil K. (1987). "A test for normality of observations and regression residuals". *International Statistical Review* **55** (2): 163-172.

B-Appendix: HRI values – 1961-2008

HRI values, 1961-2008 for countries in which HRI declines and low points corresponded to conflict events. Many other countries had declining HRI values but without a corresponding conflict event, and many conflict events that did occur in countries did not have a corresponding decline in HRI value.



C-Appendix: Building the Dynamic Version of the Human Resilience Indicator

Len Malczynski

The HRI is calculated based upon historical data, primarily from the United Nations. The historical data spans a period between 1961 and 2008 for a subset of 154 of the world's countries. The HRI is calculated by performing a mathematical transformation of the data values (see Appendix A). This calculation is termed the non-dynamic HRI. The non-dynamic HRI is also calculated for the time period from 2009 to 2030 based upon projections of data from the UN. Some of the data have not been projected, e.g. surface area of a country.

This section describes the research effort to perform a dynamic HRI calculation. The dynamics come from the model's ability to project data into the future from a starting condition. When this projection is made using 1961 as the base year it is termed the calibration (or historic) run. The HRI is also calculated using 2008 as the start year. That run is termed the dynamic run. The data projections are based upon feedback established in the model between caloric intake, freshwater per person, population density, arable land per capita and the population growth rate for each country. The previously mentioned variables are compared to a starting value and the corresponding ratio is used to alter the population growth rate. The strength of the relationship between the ratio of a variable and its starting value to the population growth rate is established with dimensionless multipliers[8].

Dimensionless multipliers are used to explicitly establish a relationship between the current value of a value in time and some fixed value. An example of this technique is carrying capacity. Carrying capacities in the real world tend to bring a growing population to a limit over time. Carrying capacity is the ratio of population to a fixed land area or some other resource such as food supply. As the ratio of population to the other variable changes an explicitly defined response curve is used to alter the population growth rate. A feedback system of this type is termed a negative feedback loop. Negative feedback loops tend to drive a variable to a limit over time (see Figure C-1).

[8] Dimensionless additives are also used in system dynamics models. A complete discussion of the relative advantages of multipliers and additives can be found in Chapter 13, Modeling Decision Making in Business Dynamics: Systems Thinking and Modeling for a Complex World, John Sterman, McGraw-Hill, 2000.

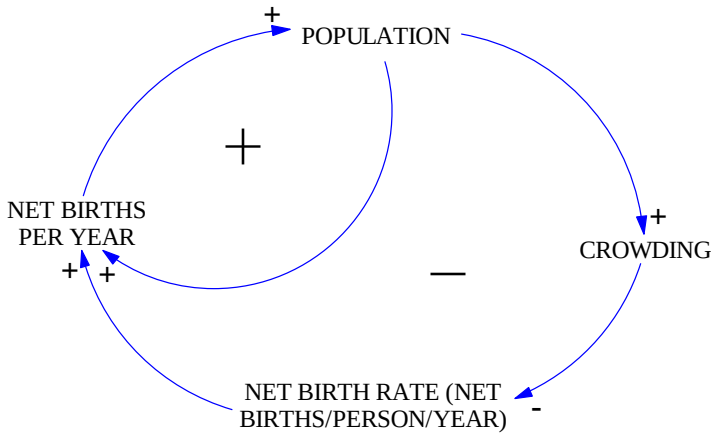


Figure C-1. A loop that controls population. Adapted from Figure 2.9 in The Lifecycle of Economic Development, Nathan B. Forrester, Wright-Allen Press, 1973.

In Figure C-2, land area is implied as a constant in order to determine the value of CROWDING. The signs on the arrow heads represent the causal direction specified by the variable at the arrow tail. In this case an increase in the CROWDING value decreases the value of NET BIRTH RATE. The strength of the decrease is specified by a dimensionless multiplier. The dimensionless multiplier value is determined from an explicit functional relationship that describes the relationship between the ratio (e.g. crowding as population divided by land area) and a corresponding multiplier.

In general multiplier functions are monotonically increasing or decreasing functions of a ratio[9]. The creation of these functions depends upon the nature of the variable ratio. Each of the four multipliers is described below.

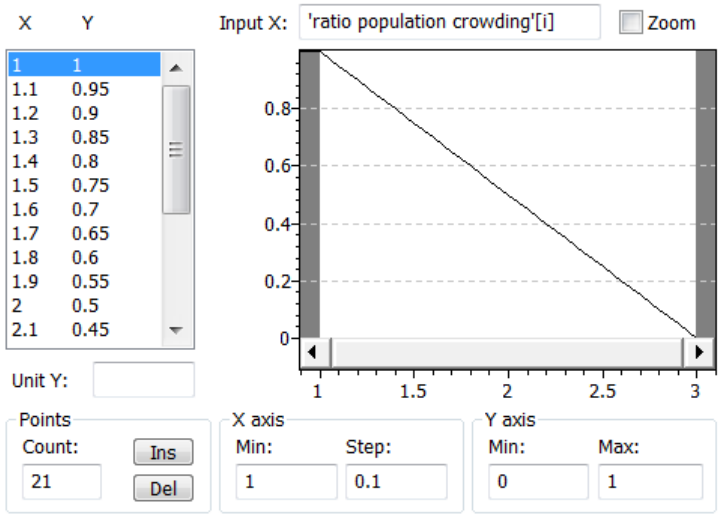


Figure C-2. Effect of population crowding multiple on population growth rate

[9] There are excellent descriptions of multiplier and additive creation in Sterman, 2000 and Fisher 2005, Modeling Dynamics Systems: Lessons for First Course.

This relationship applies to crowding. Crowding is measured by the ratio of the current population to the 2008 population. The 2008 population is a given, no matter what degree of absolute or relative crowding that implies. This ratio proceeds from 2008 to decrease the multiplier from 1 to 0 as the ratio increases from 1 to 3[10].

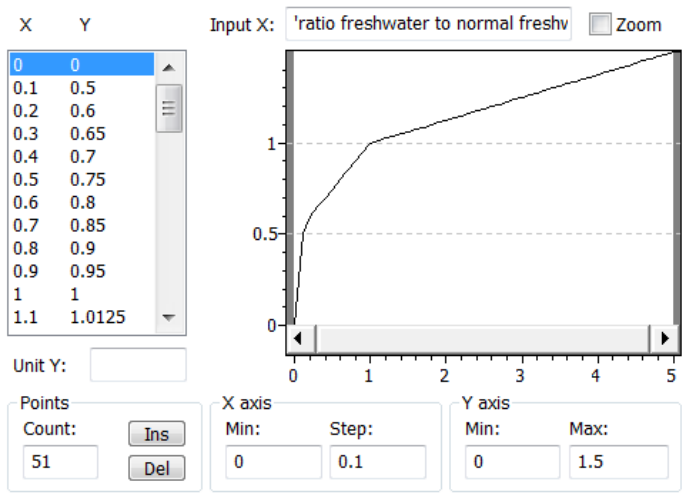


Figure C-3. Effect of freshwater per person on population growth rate

Freshwater values are static for the non-dynamic and dynamic models. Of course this ignores the effects of pollutants on water quality and water flow diversions outside a country's boundary. This ratio is driven by the increasing population which decreases freshwater per person. As the freshwater per person approaches relative extreme values it has less and less impact on population growth.

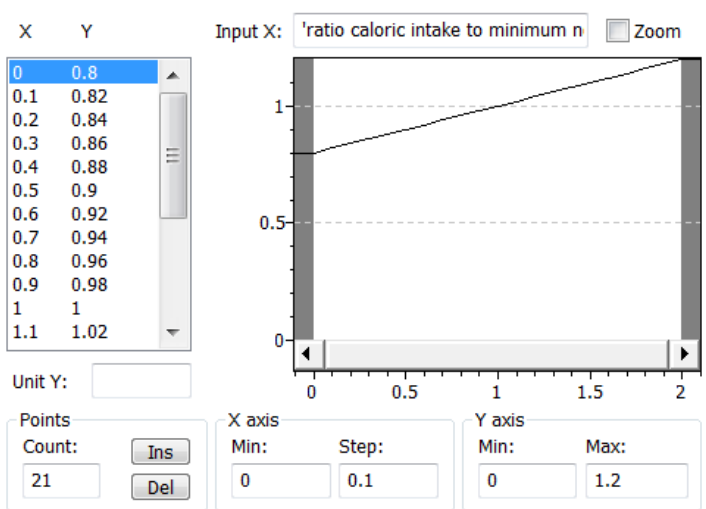


Figure C-4. Effect of caloric intake on population growth rate

[10] There are special considerations for what value the multiplier should take when the ratio value is outside the bounds of the horizontal axis. In this model the multiplier uses a horizontal asymptote. The edge values are returned when the ratio is outside the defined bounds.

Caloric intake per capita is based upon the ratio of existing caloric intake to a minimum normal caloric intake. Those data were obtained on a per country basis. Missing data were completed by taking regional averages. Note that the caloric intake values themselves are changed by another multiplier, ‘effect of arable land per person on caloric intake’ described in the next section. Caloric intake may also have a negative effect on the population growth rate. Obesity and obesity induced disease was not considered.

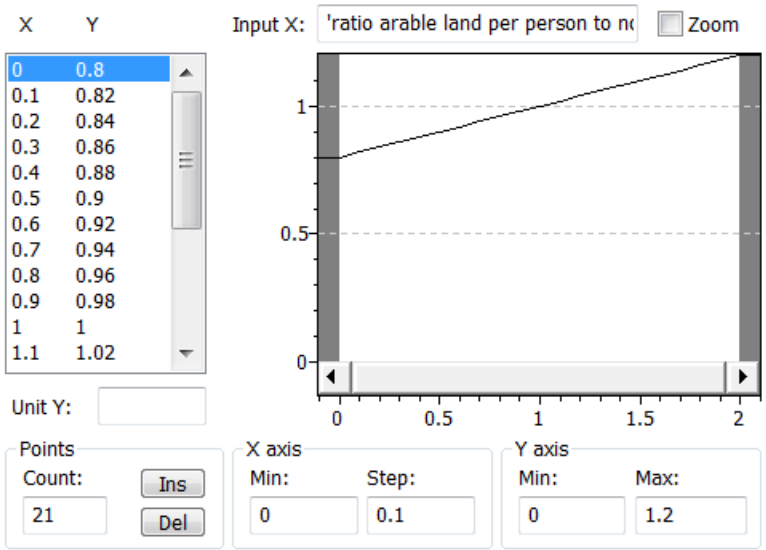


Figure C-5. Effect of arable land per person on caloric intake

This ratio, much like the population crowding ratio, is based upon 2008 starting values. Arable land is fixed for the duration of the model runs (1961 to 2030). We did not have enough credible data to alter the arable land value over time due to pollution, salt accumulation, etc. Again, using the same functional relationship for all countries cannot include food aid, droughts, crop diseases, etc.

The actual values assigned to the functions are not as important as the slope of the relationship. At the scale of 154 countries it would be impossible to develop these relationships specific to each country. In the current model the same relationship is applied to all countries.

Each of the multipliers is lagged for some period of time since populations are not immediately aware of the change in these values through time. The final equation is defined as:

'current population growth rate’
* 'delayed effect of caloric intake on population growth rate'
* 'delayed effect of freshwater per person on population growth rate'
* 'delayed effect of population crowding multiple on population growth rate'

Causally this equation is described in Figure C-6.

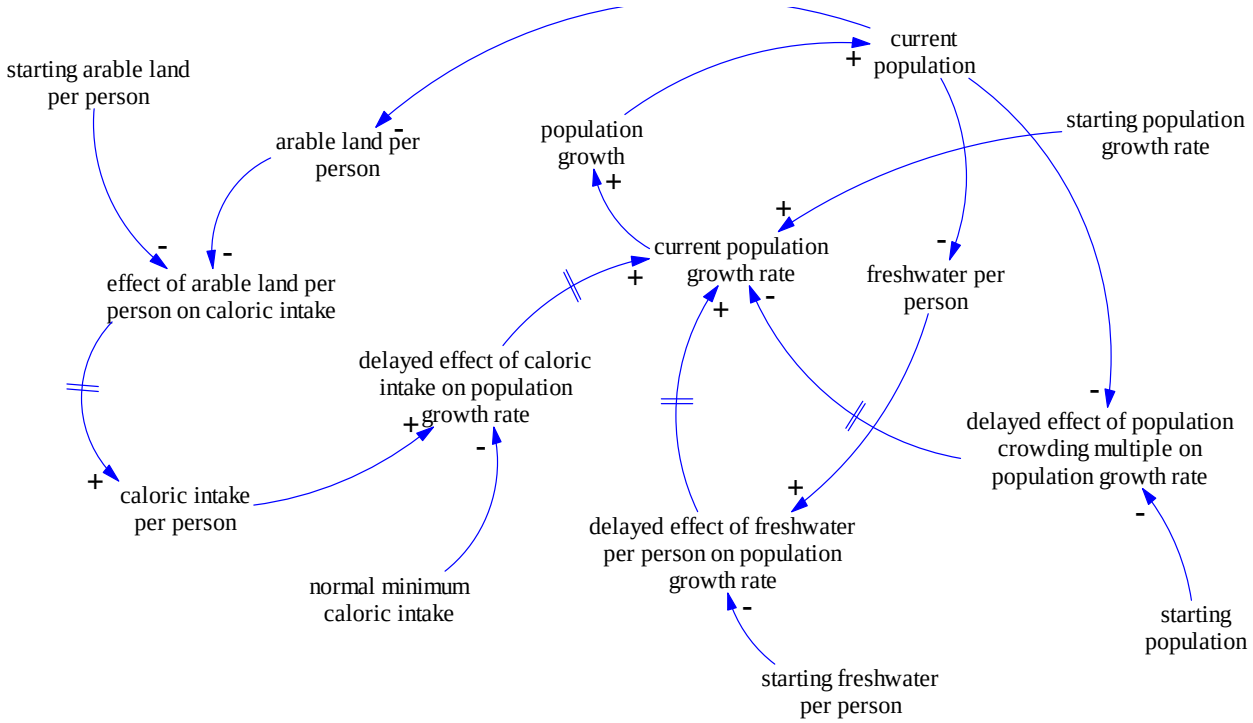


Figure C-6. Feedback effects on population growth rate in the dynamic HRI model

D-Appendix: Variability Analysis

Table D-1. Analysis of variability among highest risk and lowest risk countries

Variability in the HRI between the lowest- and highest-scoring countries	**1961-2008**			**2009-2030**		
	Standard Deviation	Range	Intra-Annual Difference	Standard Deviation	Range	Intra-Annual Difference
15 Lowest Scoring Countries	0.15	0.55	0.031	0.035	0.11	0.0083
15 Highest Scoring Countries	0.071	0.24	0.014	0.027	0.090	0.0045

All values are year,country averages. "Intra-Annual Difference" is calculated as HRI_{t+1} *-* HRI_{t} *where t is each year of the calculation from 1961 to 2029.*

E- Appendix: HRI Correlation with Conflict Datasets

Daniel Villa

The HRI index is postulated to be an indicator of an increase in the presence of conflict due to poor conditions for human resilience. This postulate has been statistically tested by aligning data with two conflict type data sets. Both of these datasets are not proven to be comprehensive but do capture a very wide range of conflict types over a large set of the 154 HRI countries.

The first is from the Uppsala Conflict Program Armed Conflict Dataset (UCDP)[11] version 4-2012 created by Gleditsch, et al. (2002) and maintained by Themnér & Wallensteen (2012). As described by Themnér (2012) in the UCDP codebook, conflict in this database is defined as an event which requires involvement of at least one official governing body and involves the death of more than twenty-five people. The analysis performed divides the HRI index range into ten bins and divided the total number of data points in each bin by the number of data points which did have conflict. The HRI countries were aligned to the conflict Location. This ratio is the probability that a given country is in a state of conflict if it falls within the range of a given bin. The left hand upper side of Figure E-1 shows the results with an upper and lower bound. The real world statistic which includes all unknown data probably falls between these curves. The left hand lower side of Figure E-2 shows the number of data points in each bin. Bins with less than one hundred data points were not considered statistically significant and were excluded from the probability curve. There is a very clear decrease in the percentage of conflict in the range of statistical significance for the HRI index. This result is strong evidence that a decreasing HRI score indicates an increased probability of the development of a major government based conflict either between countries or due to internal strife. This result does not tell how often low HRI causes conflict since more information is needed to deduct causation.

The second analysis uses the Militarized Interstate Dispute (MID) data set compiled by Ghosen, et. al. (2004) version 3.10. This data set only reached to the year 2000 and therefore had less eligible data points. It allows a much broader range of "disputes" which include non-violent conflict which involves militarization of a government's forces. Disputes are defined by Jones et. al. (1996) as, "composed of incidents that range in intensity from threats to use force to actual combat short of war." By definition disputes therefore exclude much of the data contained in the UCDP database, though some overlap is expected. A dispute can include a threat to use force, threat to blockade, threat to occupy territory, threat to declare war, or a threat to use nuclear weapons as discussed in Jones, et. al. (1996). The complexity of the data set is a little more involved and captures escalation of disputes. The much data set also has multiple entries of all of the countries involved in the dispute. This is unlike the UCDP analysis since the geographic location is not as prominent[12]. The presence of any dispute that a nation was involved in for a given year was taken as a positive data point. The same analysis on the MID data produces no significant trend in sensitivity between disputes and the HRI. This may be because disputes occur more often between high HRI countries in low HRI countries and that high HRI countries also have considerable power to initiate disputes in order to manipulate weaker nations. Either way the nature of the disputes probably needs further investigation to classify the location of the

[11] http://www.pcr.uu.se/research/UCDP/

[12] UCDP captures multiple nation involvement but centers around the location of the conflict.

dispute more consistently. The lack of a trend may be simply revealing that HRI is not an indicator of disputes, which can be entirely non-violent, but is a good indicator of conflict which must be violent. Further analysis which filters the MID disputes in a different way may be needed.

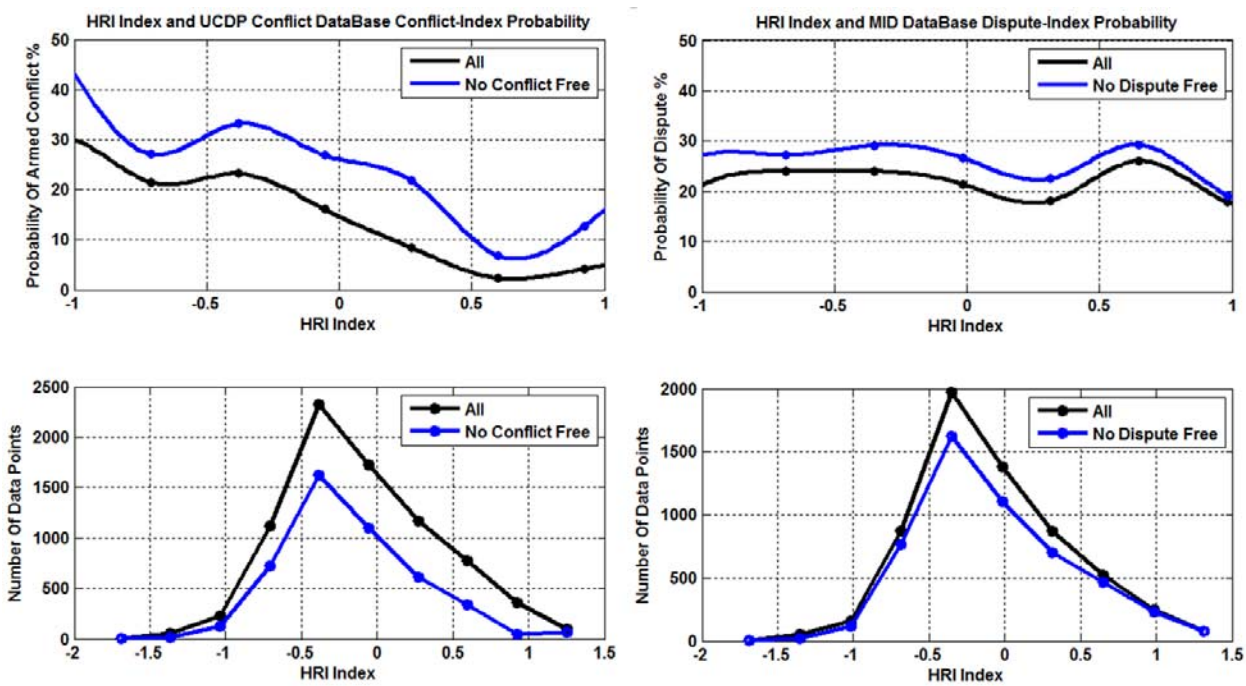


Figure E-1. HRI index versus probability of conflict based on the UCDP conflict dataset[13] and for the MID dispute database

References

Gleditsch, Nils Petter; Peter Wallensteen, Mikael Eriksson, Margareta Sollenberg & Håvard Strand (2002) Armed Conflict 1946–2001: A New Dataset. Journal of Peace Research 39(5): 615–637

Themnér, Lotta & Peter Wallensteen (2012) Armed Conflict, 1946-2011 Journal of Peace Research 49(4)

Themnér, Lotta (2012) UCDP/PRIO Armed Conflict Dataset Codebook

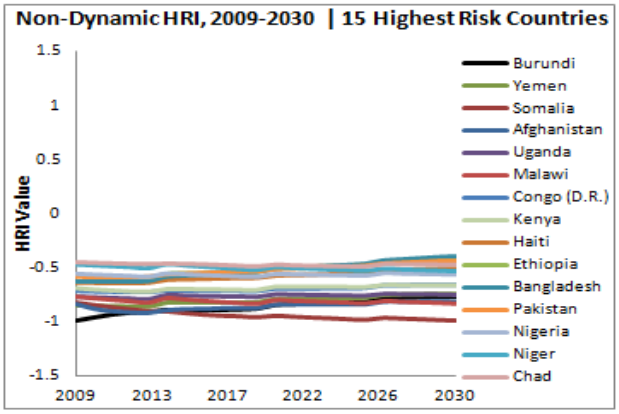
[13] This is a comparison of 1961 to 2011 data of the Uppsala Conflict Data Program Armed Conflict Dataset (UCDP) and the Human Reslience Index. The conflict data is known to not be comprehensive. This is especially true for countries with low incomes and poor conditions whose records tend to be less thorough (Themnér 2012). "All" signifies that all data was used regardless of whether a country is conflict free. "No Conflict Free" is the data if all conflict free countries are excluded. This would tend to cause false entries of zero conflict for countries with poor conditions to be eliminated from the dataset. It probably leads to the elimination of countries with good conditions which are actually conflict free though (thus the bulge to the far right). If all data were known, the actual statistic is highly likely to be between these curves

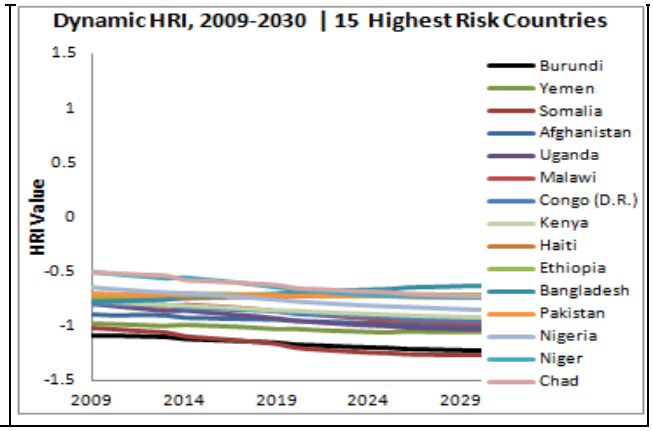
Ghosn, Faten, Glenn Palmer, and Stuart Bremer. 2004. "The MID3 Data Set, 1993–2001: Procedures, Coding Rules, and Description." Conflict Management and Peace Science 21:133-154.

Jones, Daniel M, Bremer, Stuart A., Singer, David J., (1996) "Militarized Interstate Disputes, 1816-1992: Rationale, Coding Rules, and Empirical Patterns," Conflict Management and Peace Science, 15(2): 163:213.

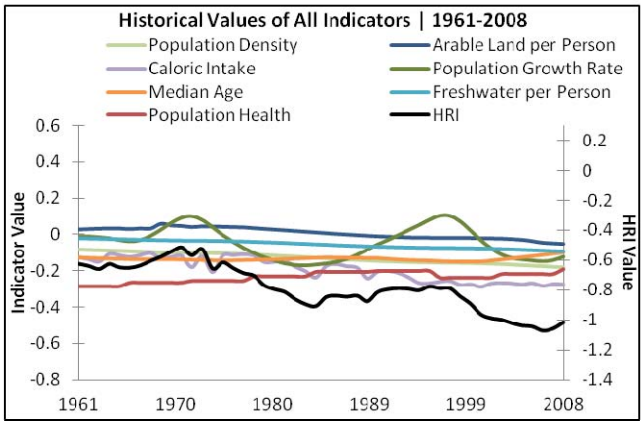
F- Attachment: Supplemental Information

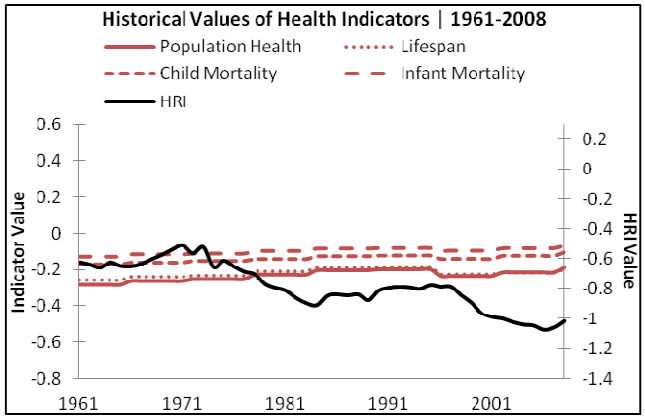
Non dynamic and dynamic results, 2009-2030, for 15 highest risk countries

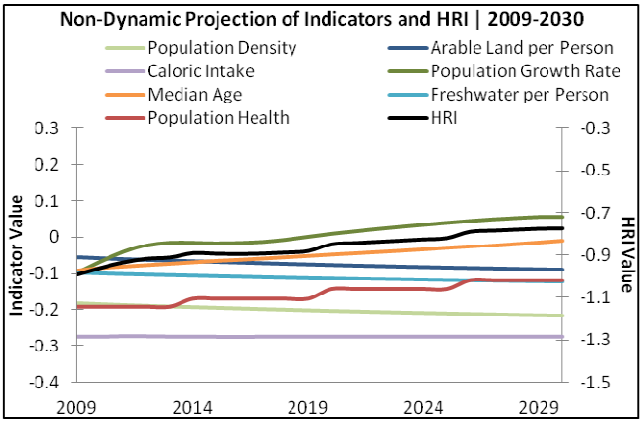


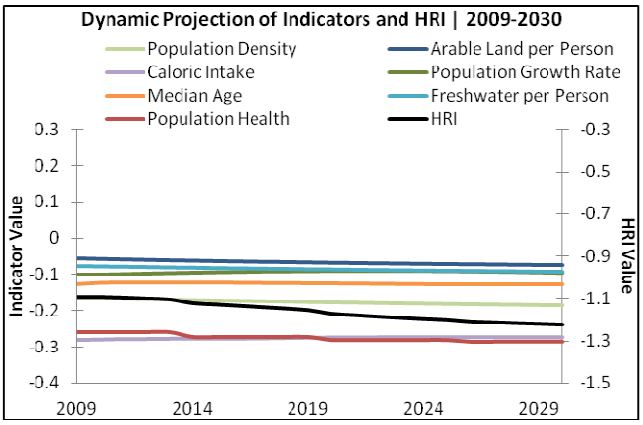


BURUNDI









HRI and indicator values, and non-dynamic and dynamic modeling results, 2009-2030.

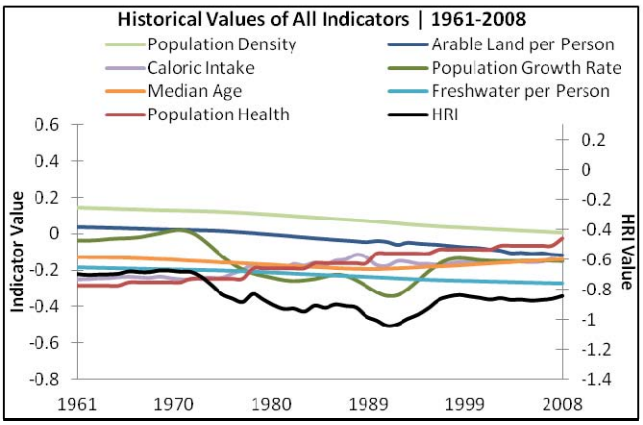
The graphs in this section show individual indicator values and results from both non-dynamic and dynamic HRI modeling, 2009-2030. These graphs show which indicators are having impacts on the HRI.

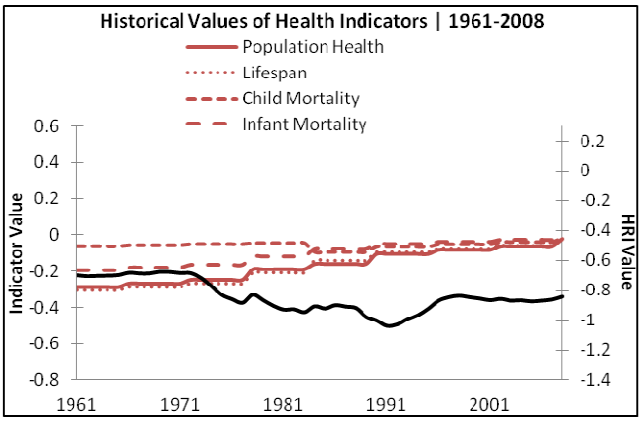
Careful study of the graphs on this and the following pages will show that there is inconsistent correspondence between the results of the non-dynamic and dynamic models. One possible explanation for this is that in the dynamic model functional relationships between variables and indicators are constant across all 154 countries in the analysis (See Appendix C). For some countries, those functional relationships may match the real relationships reasonably well, and in that case we might expect to see greater correspondence between the non-dynamic and dynamic results. However, if the functional relationships used in the dynamic model poorly match the real relationships in a particular country, then we might expect to see divergence among the results.

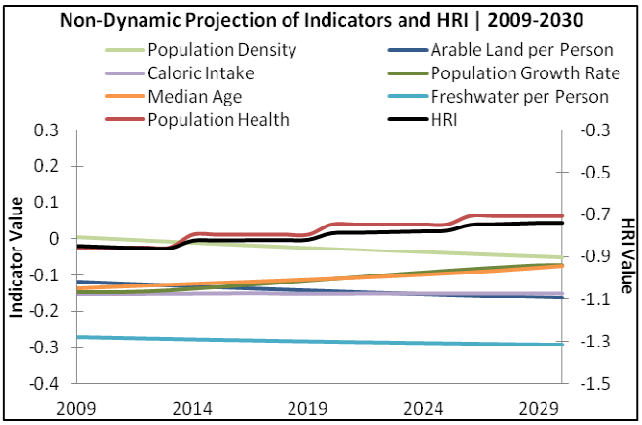
One might also notice that in some cases the 2009 starting points for the different indicator values and the HRI value are different. This is because data transformations used to normalize data distributions were done one way in the non-dynamic model and another way in the dynamic model.

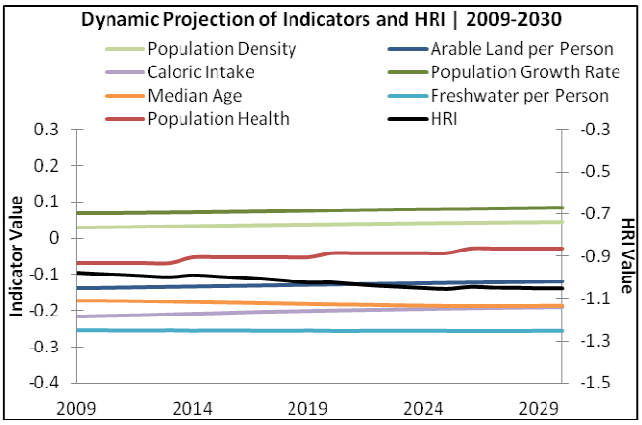
Future work on the HRIM will address both these issues.

YEMEN

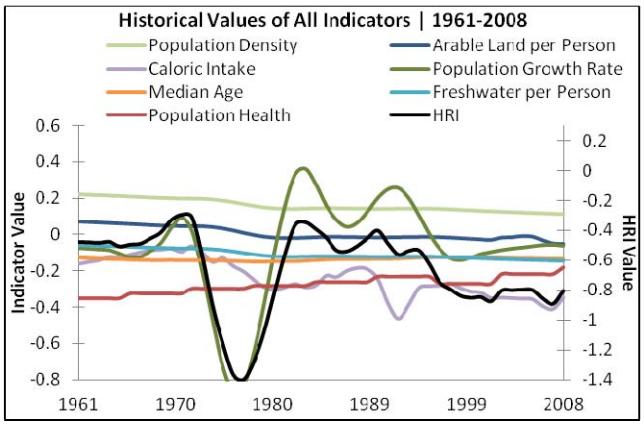

Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
1961
1970
1980
1989
1999
2008


Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
Indicator Value
HRI Value
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
-1.2
-1.4
1961
1971
1981
1991
2001


Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.3
-0.5
-0.7
-0.9
-1.1
-1.3
-1.5
2009
2014
2019
2024
2029


Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
-0.3
-0.5
-0.7
-0.9
-1.1
-1.3
-1.5
2009
2014
2019
2024
2029

SOMALIA


Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
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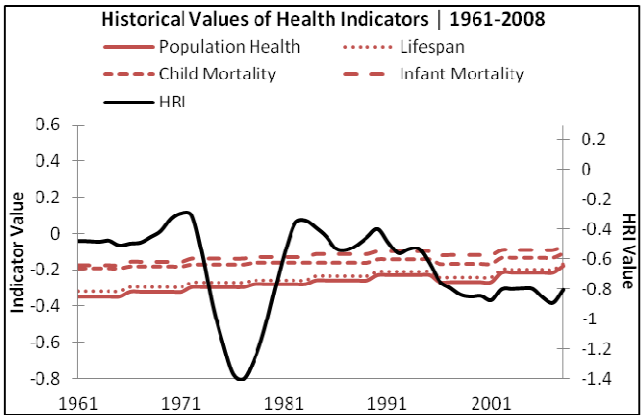
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
HRI
Indicator Value
HRI Value
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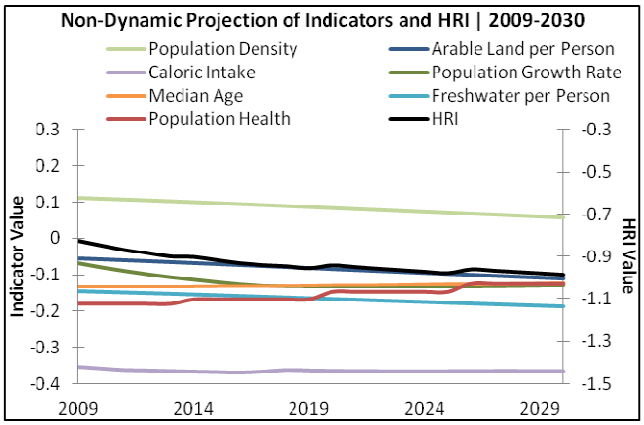
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.3
0.2
0.1
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-0.2
-0.3
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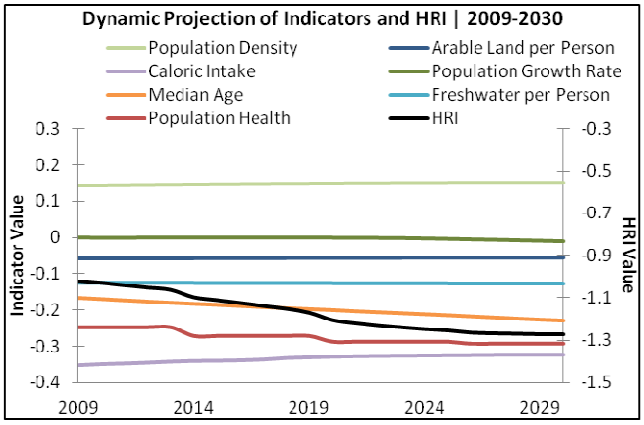
2029


Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.3
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2024
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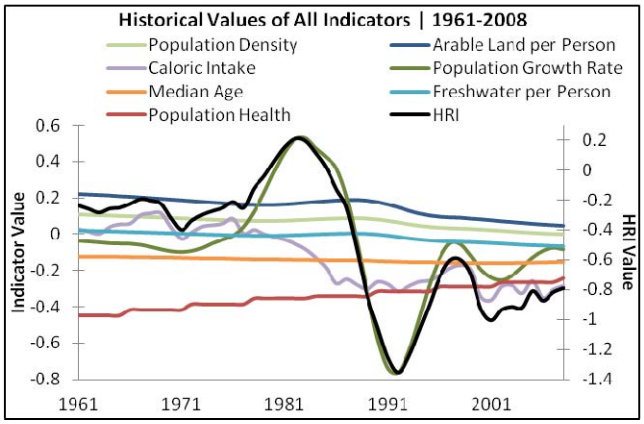
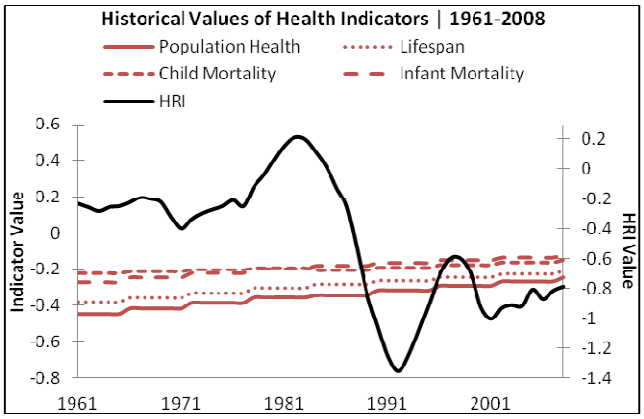
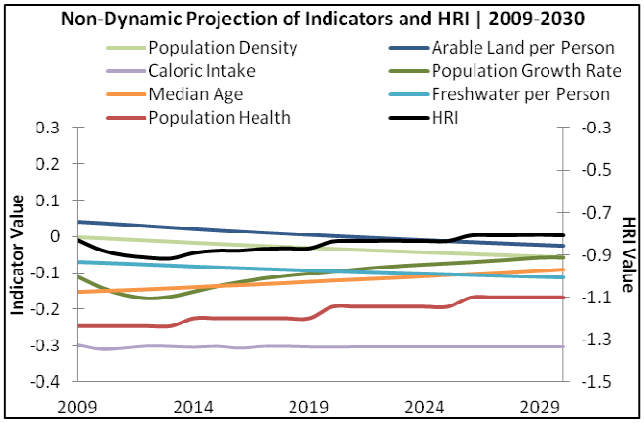
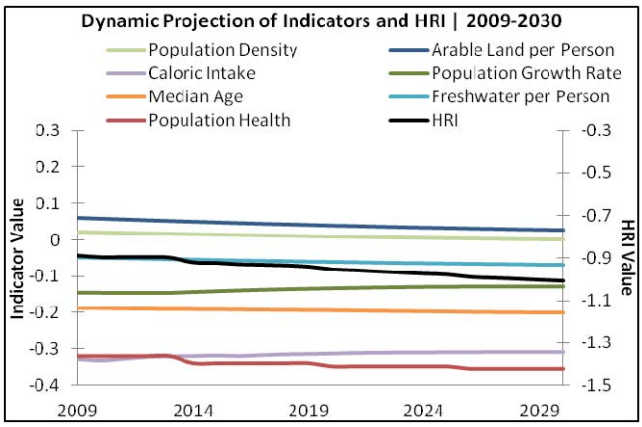
AFGHANISTAN









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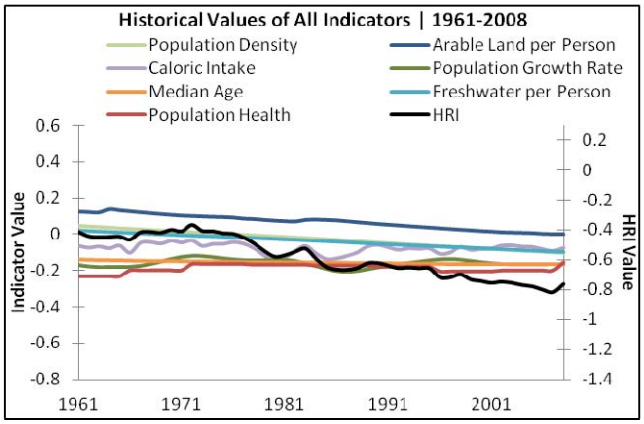
Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.6
0.4
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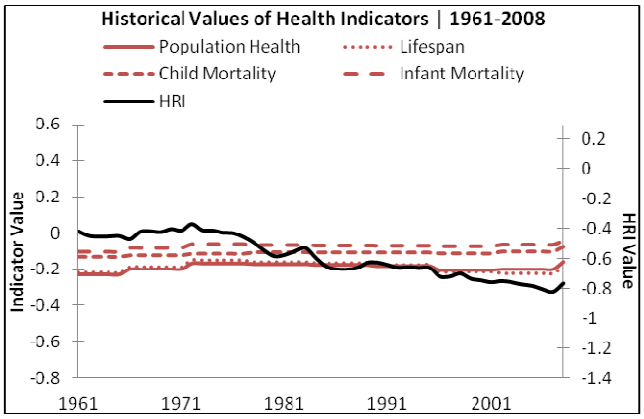
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
HRI
Indicator Value
HRI Value
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1991
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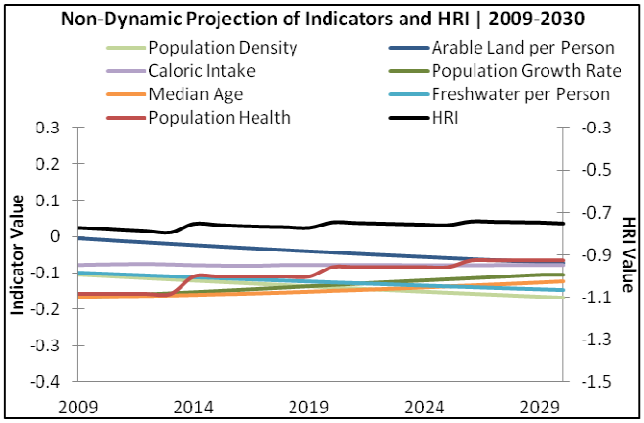
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.3
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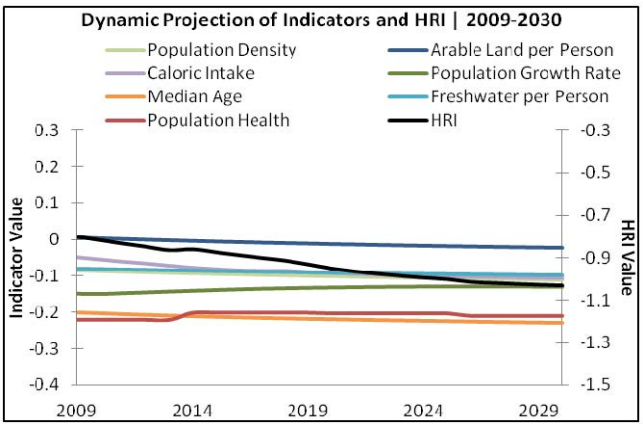
Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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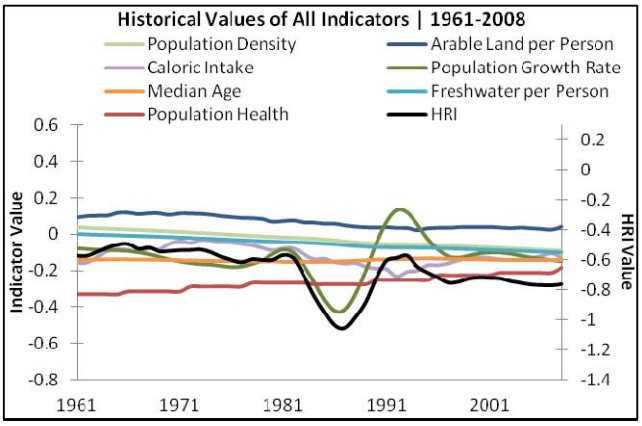
MALAWI


Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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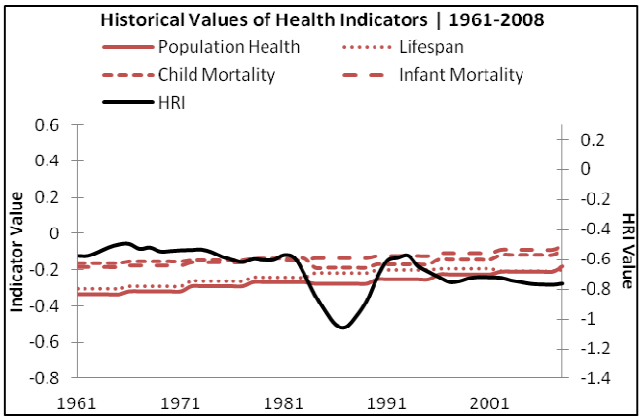
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
HRI
Indicator Value
HRI Value
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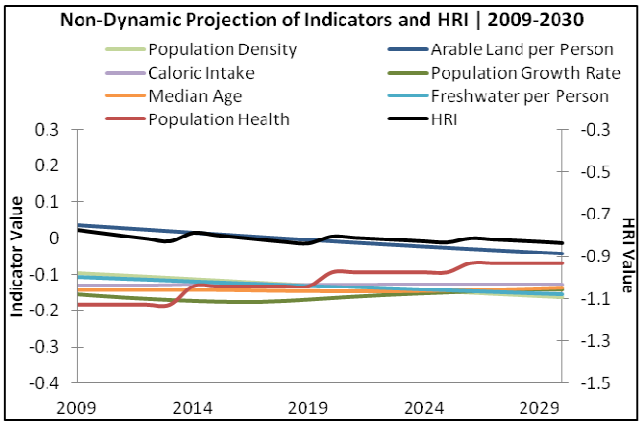
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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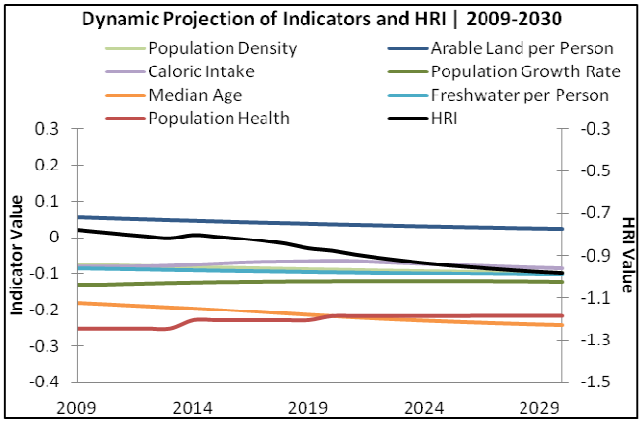
Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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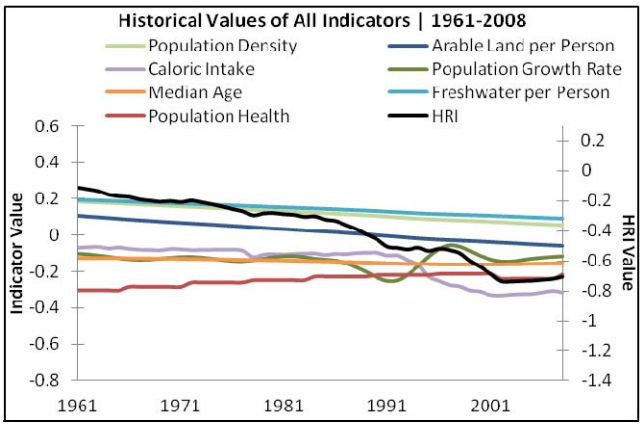
CONGO (D.R.)


Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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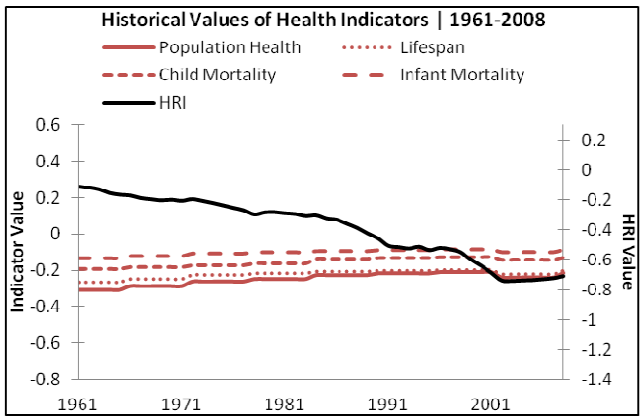
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
HRI
Indicator Value
HRI Value
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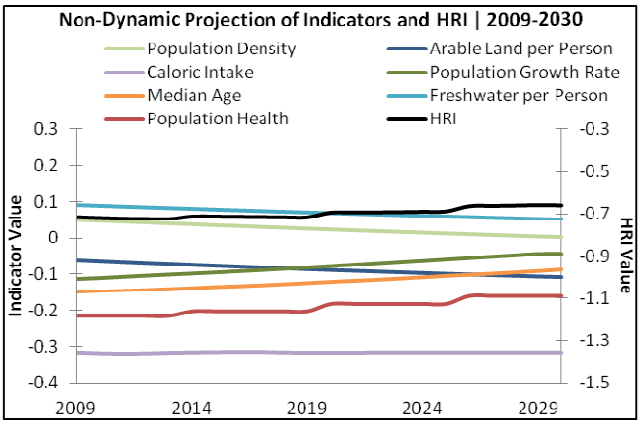
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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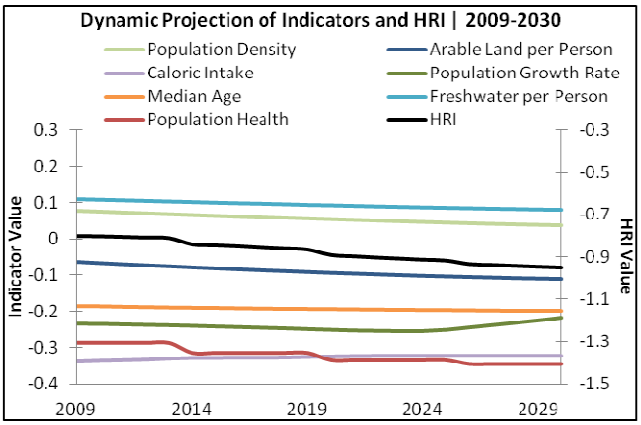
Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
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Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
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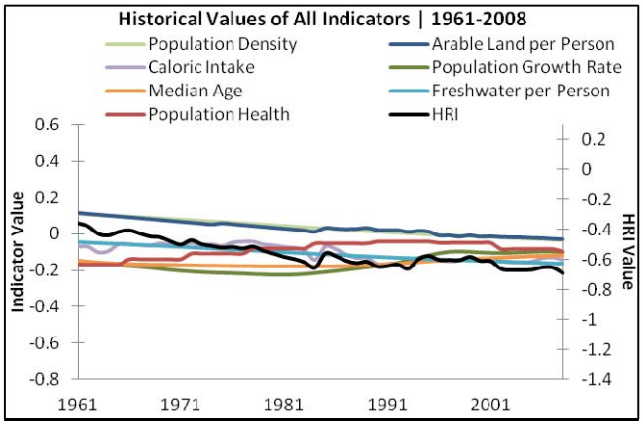
KENYA


Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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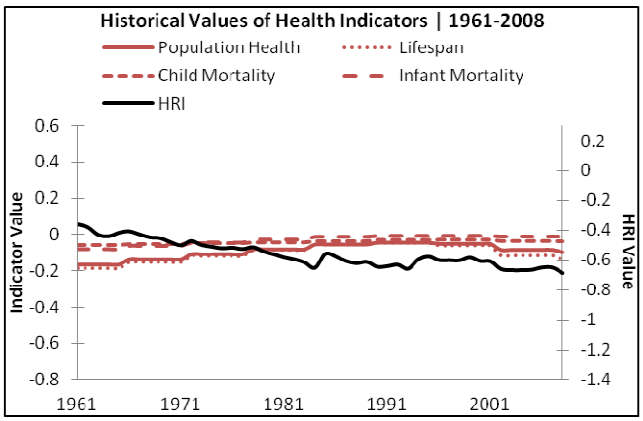
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
HRI
Indicator Value
HRI Value
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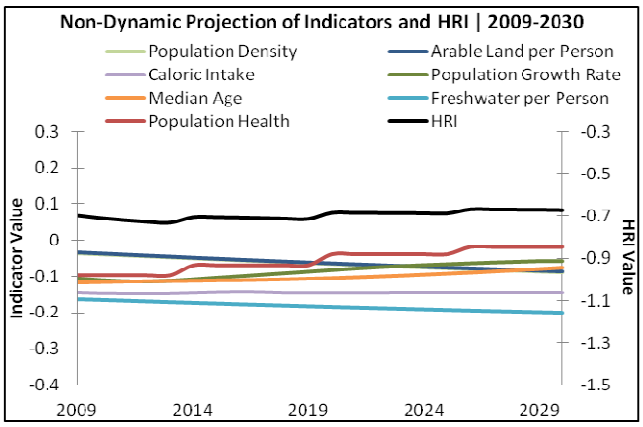
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
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Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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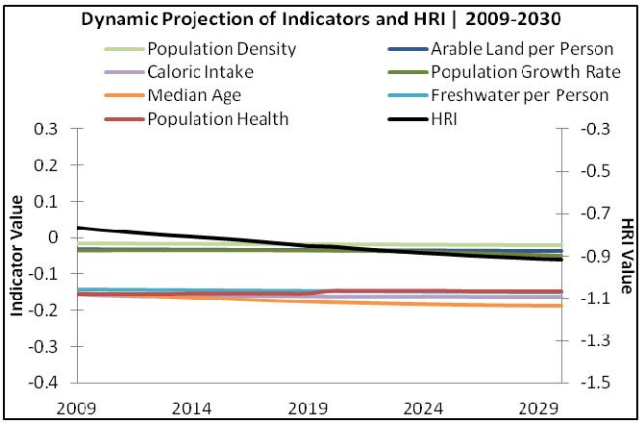
Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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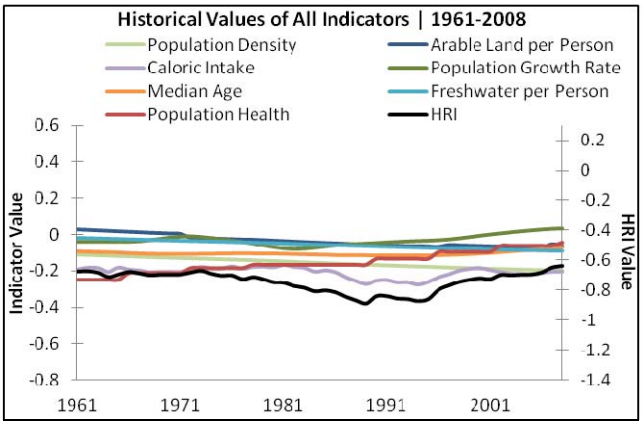
HAITI


Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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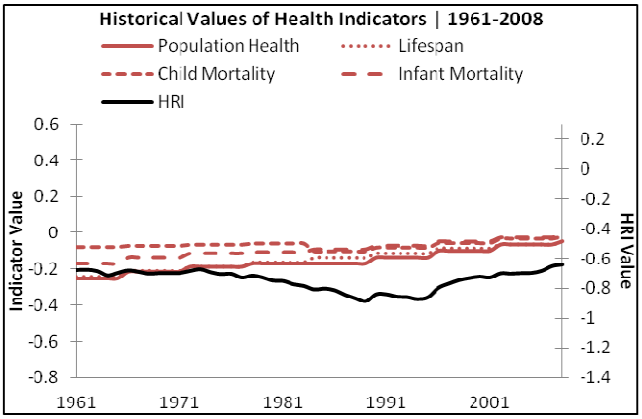
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
HRI
Indicator Value
HRI Value
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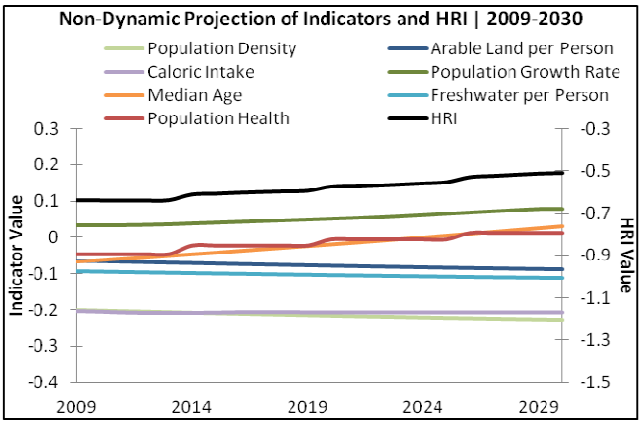
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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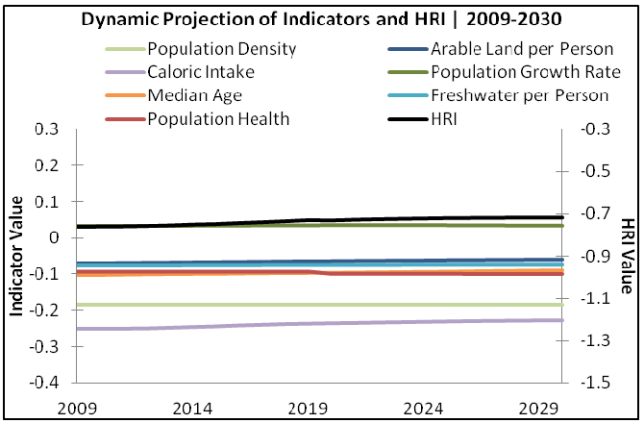
Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
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Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
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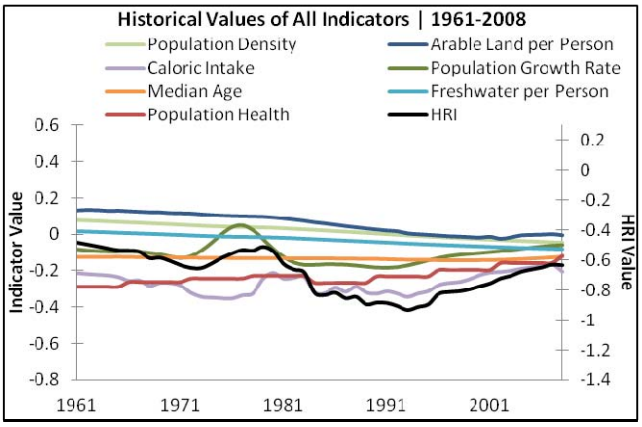
ETHIOPIA


Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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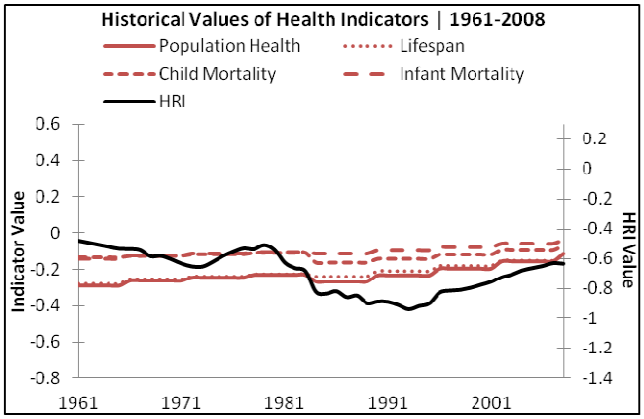
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
HRI
Indicator Value
HRI Value
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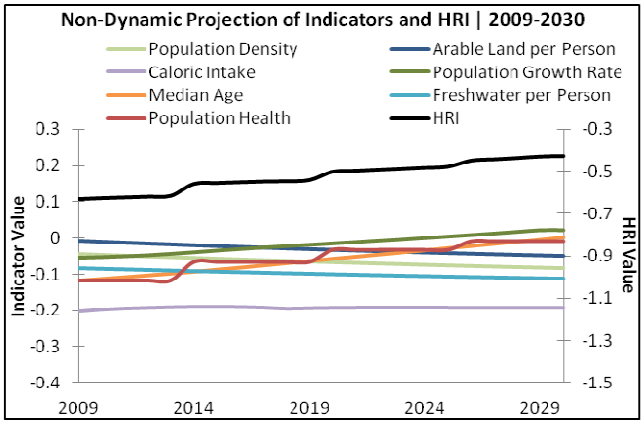
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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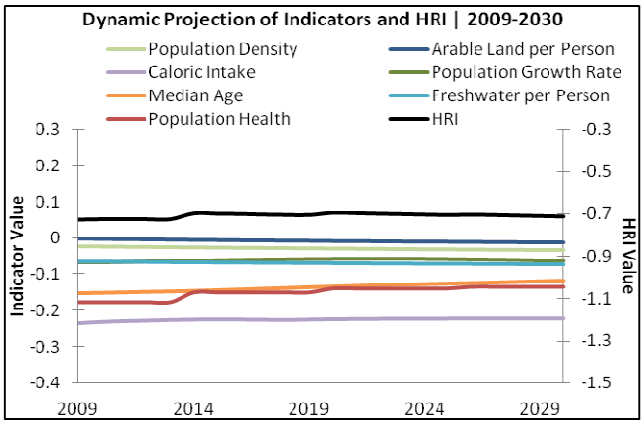
Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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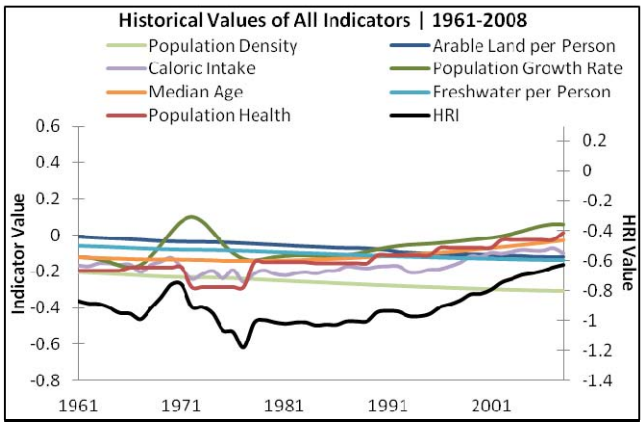
Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
0.6
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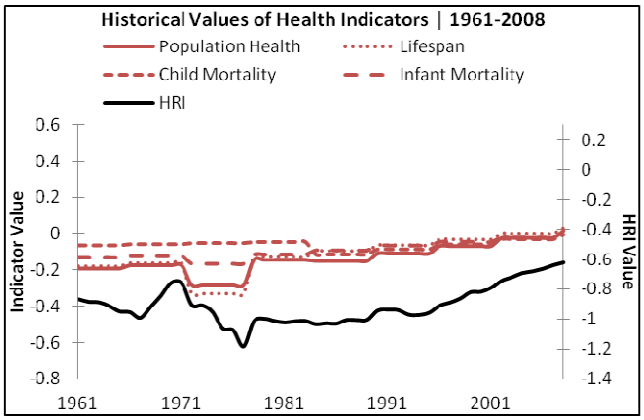
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
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Indicator Value
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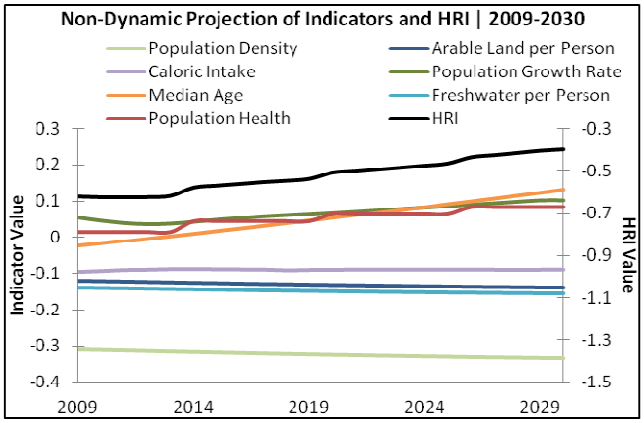
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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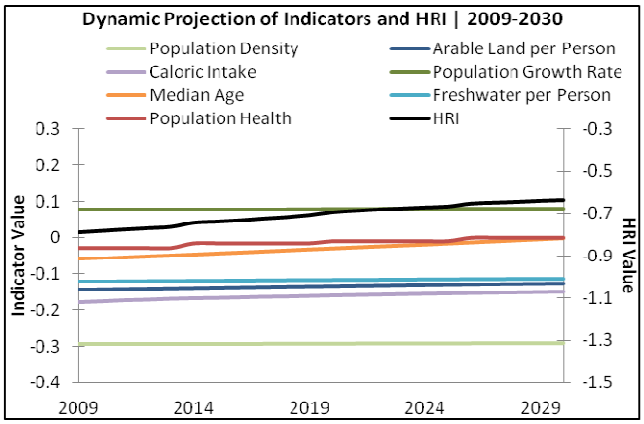
Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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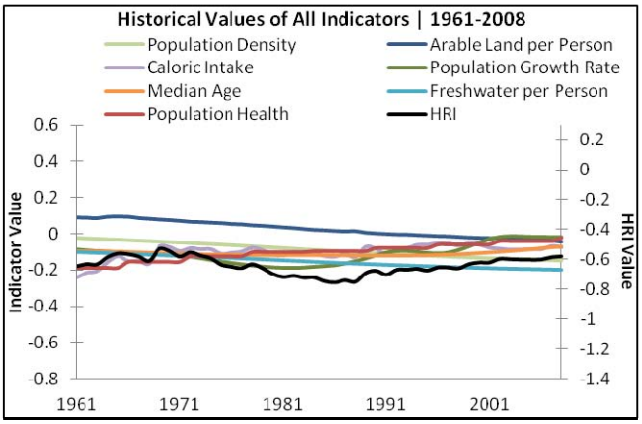
Historical Values of All Indicators | 1961-2008
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
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Indicator Value
HRI Value
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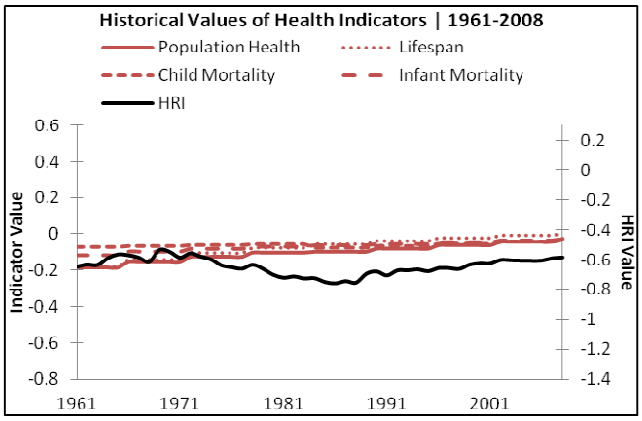
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
HRI
Indicator Value
HRI Value
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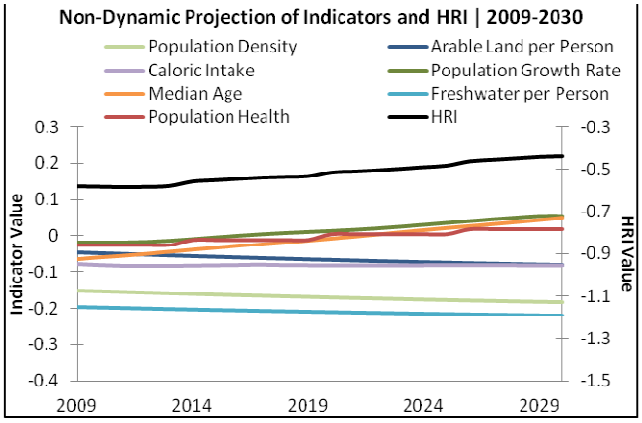
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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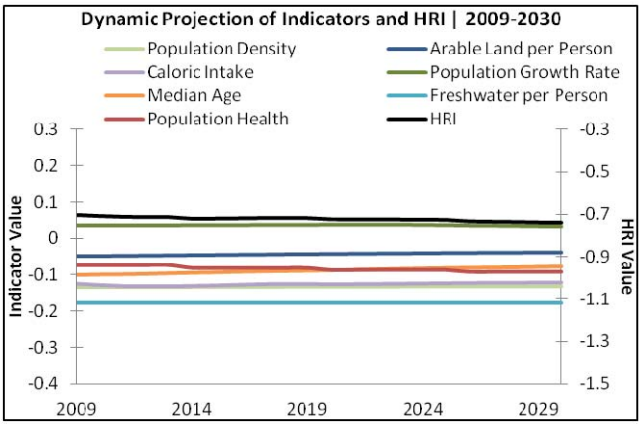
Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
Arable Land per Person
Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
HRI
Indicator Value
HRI Value
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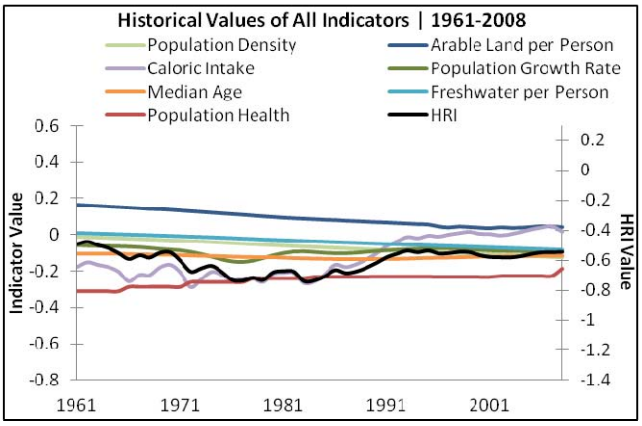
NIGERIA


Historical Values of All Indicators | 1961-2008
Population Density
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Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
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Indicator Value
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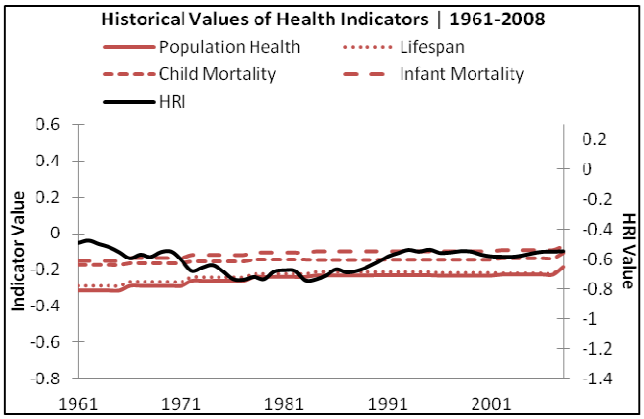
Historical Values of Health Indicators | 1961-2008
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Infant Mortality
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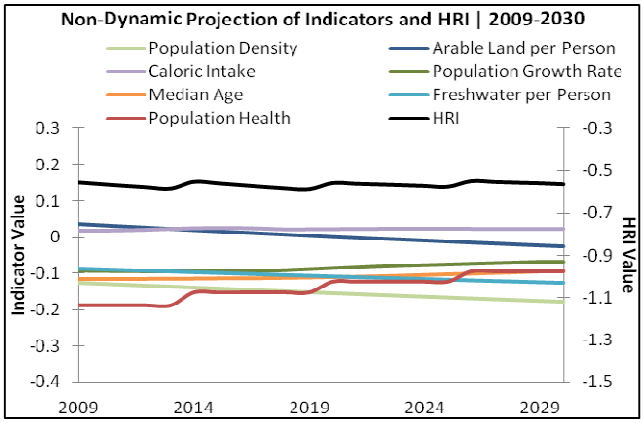
Non-Dynamic Projection of Indicators and HRI | 2009-2030
Population Density
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Caloric Intake
Population Growth Rate
Median Age
Freshwater per Person
Population Health
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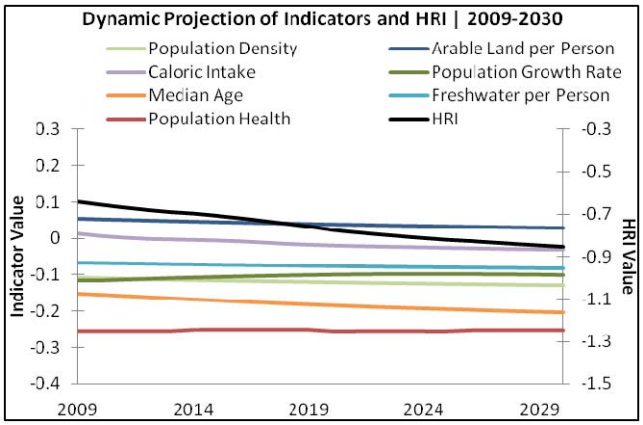
Dynamic Projection of Indicators and HRI | 2009-2030
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Population Health
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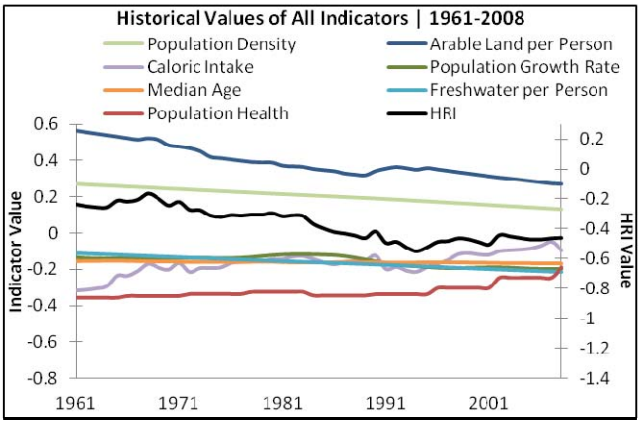
Historical Values of All Indicators | 1961-2008
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Population Growth Rate
Median Age
Freshwater per Person
Population Health
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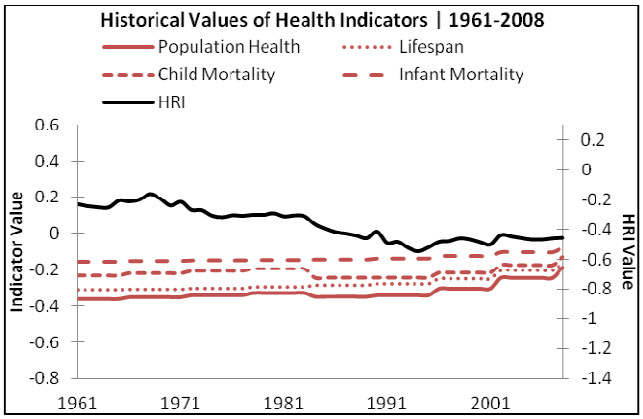
Historical Values of Health Indicators | 1961-2008
Population Health
Lifespan
Child Mortality
Infant Mortality
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Indicator Value
HRI Value
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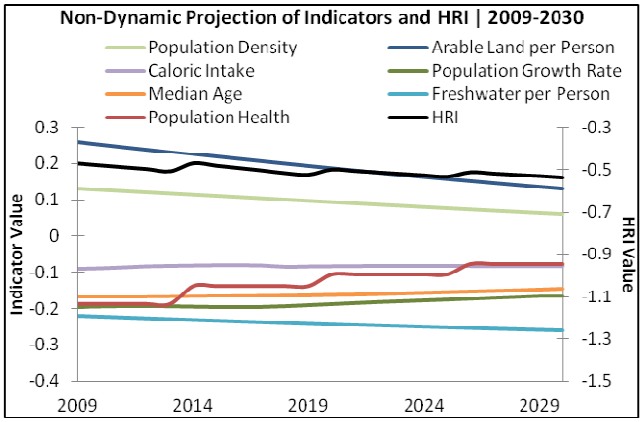
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Population Density
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Caloric Intake
Population Growth Rate
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Freshwater per Person
Population Health
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Indicator Value
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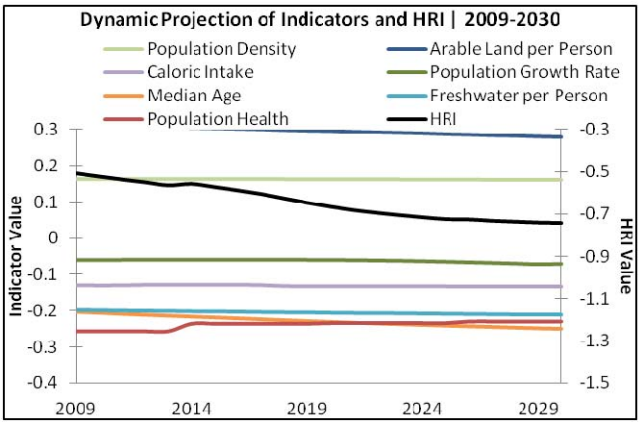
Dynamic Projection of Indicators and HRI | 2009-2030
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Population Growth Rate
Median Age
Freshwater per Person
Population Health
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HRI Value
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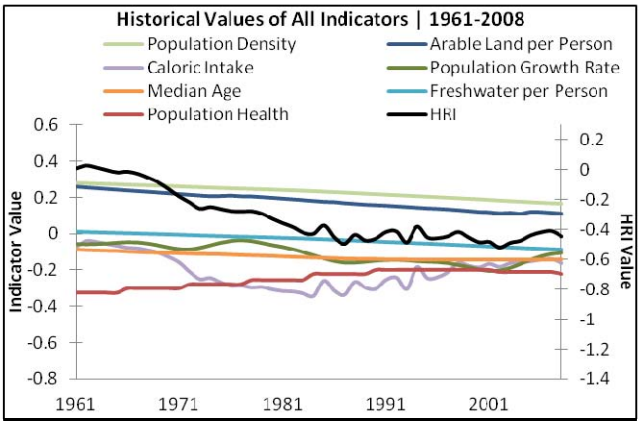
Historical Values of All Indicators | 1961-2008
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Freshwater per Person
Population Health
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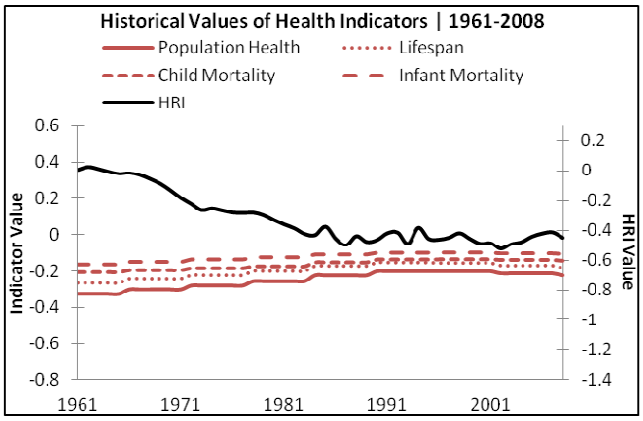
Historical Values of Health Indicators | 1961-2008
Population Health
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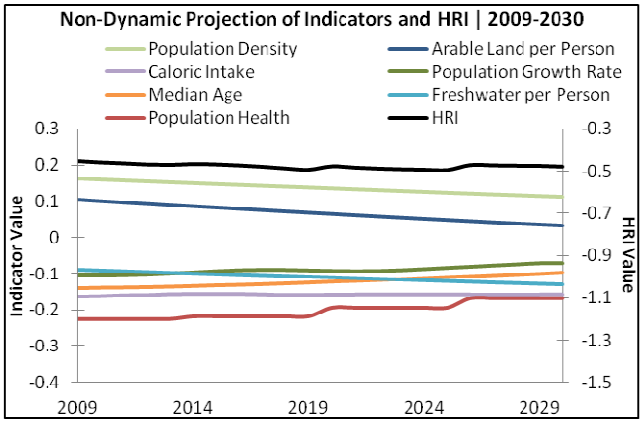
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Indicator Value
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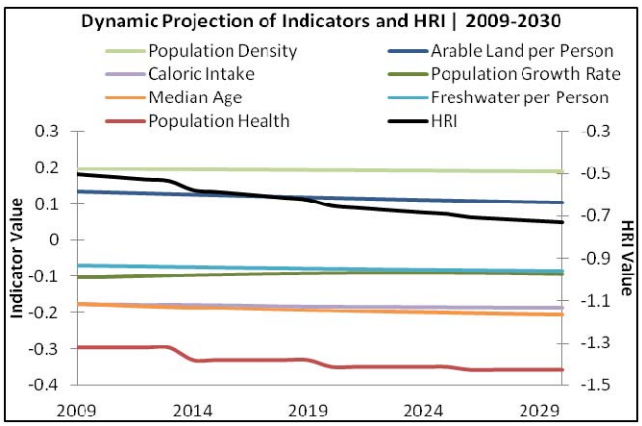
Dynamic Projection of Indicators and HRI | 2009-2030
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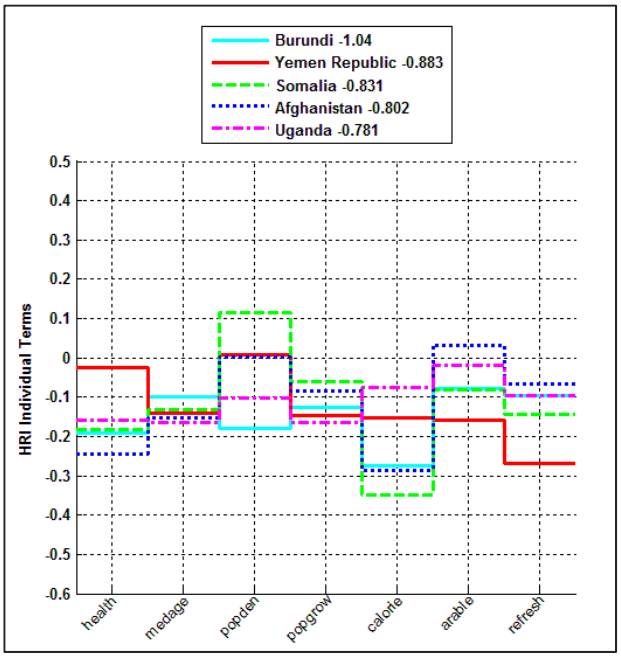
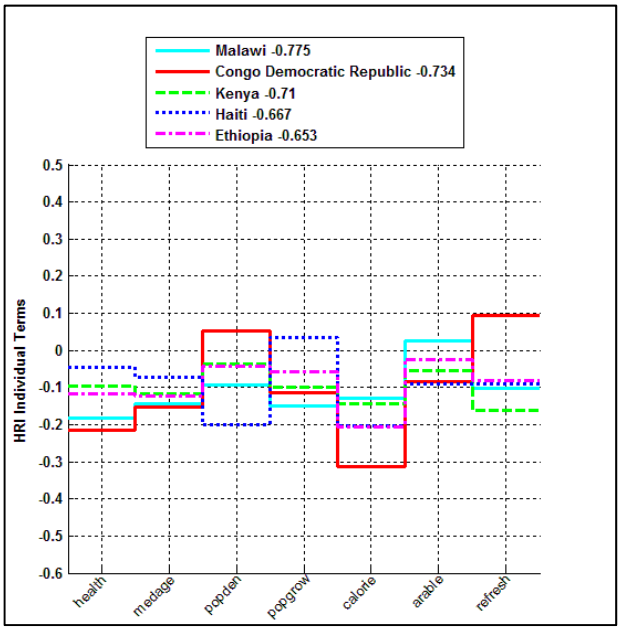
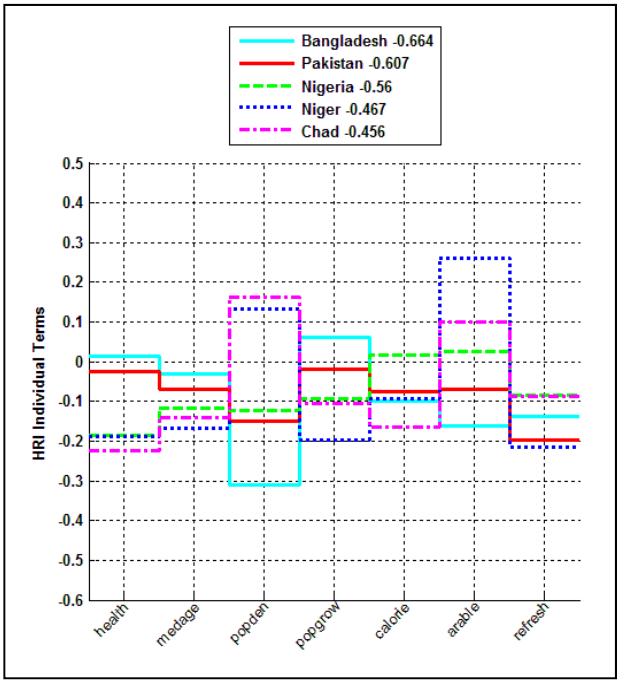
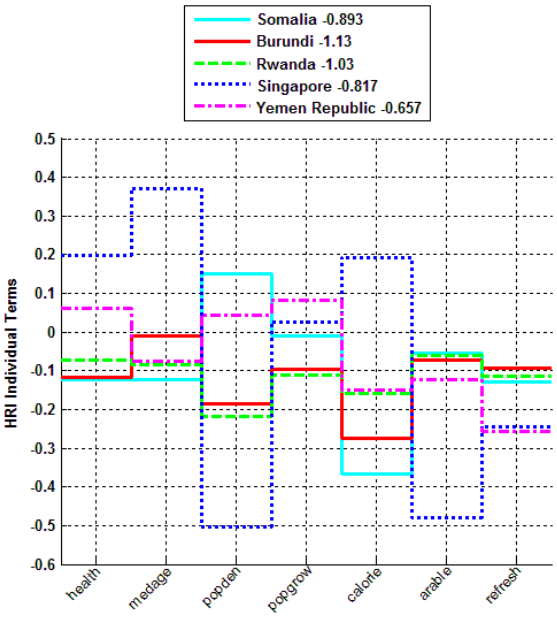
2008 highest risk countries, HRI indicator scores for post-FSI filter

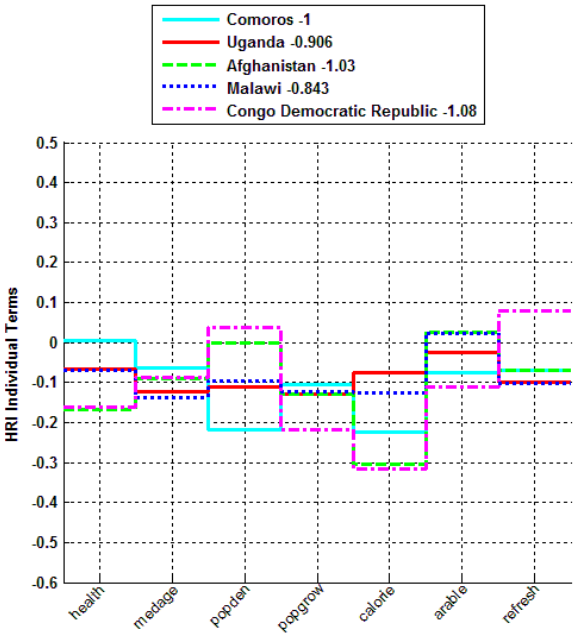


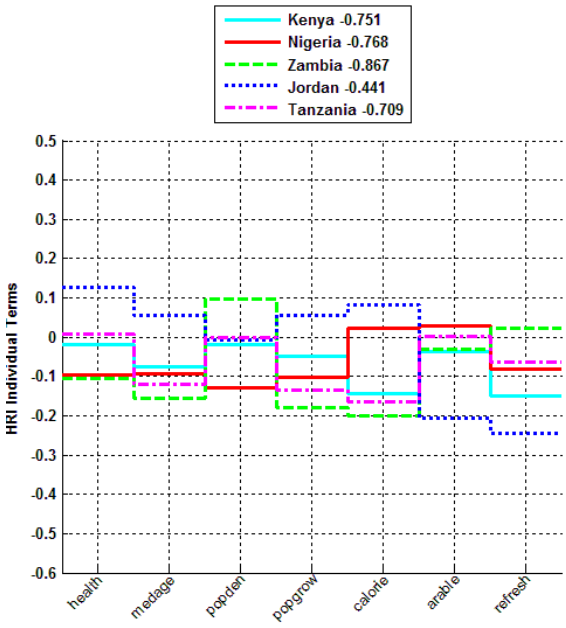




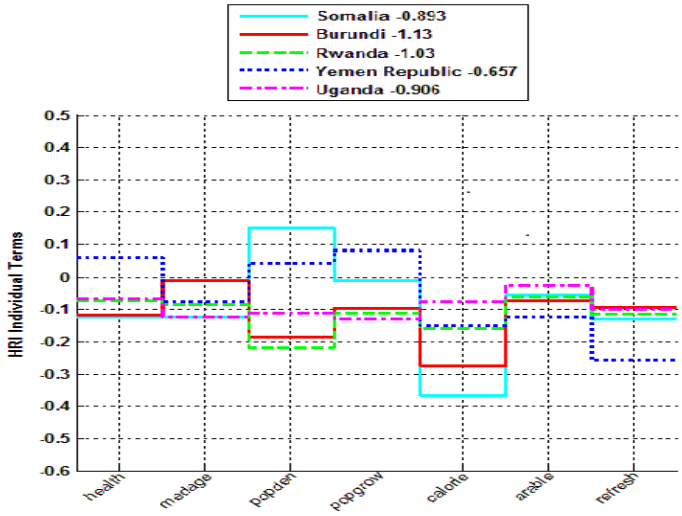
2030 highest risk countries, HRI indicator scores for dynamic results pre-FSI filter.

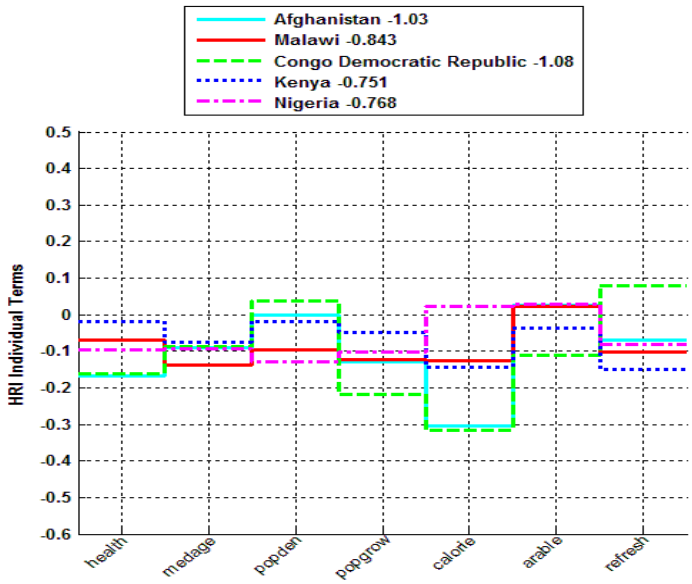


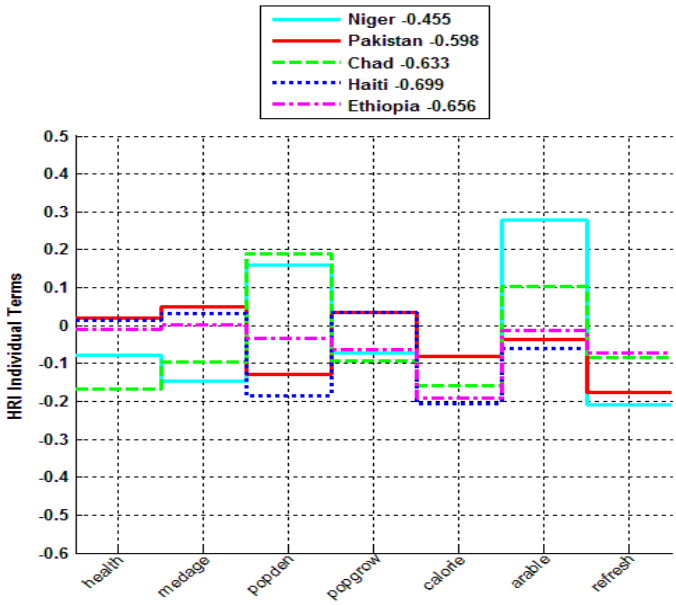




2030 highest risk countries, HRI indicator scores for dynamic results post-FSI filter.







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