Appendix

Technical Note on the Drought Impacts Model*

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How many people live in dryland zones of Sub-Saharan Africa, and what are their livelihood strategies? How many of these people are vulnerable to droughts and other shocks, and of those who are vulnerable, how many are actually affected in an average year? How are the numbers of vulnerable and drought-affected people living in drylands likely to evolve as the population increases and national economies grow and transform? To what extent can the impacts of drought be mitigated through policy interventions that improve the productivity and sustainability of livelihood strategies or provide protection in the form of safety nets? And how much would these policy interventions cost?

These questions are hard to answer, for two main reasons. First, because national statistical reporting services in many dryland countries are weak, detailed information is not always available either about the people who currently live in the drylands or about their livelihood activities. Second, because events in the drylands are influenced by a complex set of agro-climatic, demographic, economic, and political drivers, projecting future trends is technically difficult.

Despite these challenges, the team that carried out the Africa Drylands Study made an effort to quantify the scope of the challenge facing policy makers, with the objective of providing insight into the likely impacts and fiscal costs of alternative resilience-enhancing interventions. Answers to the above questions were generated with the help of a diverse set of modeling tools.

The modeling effort proceeded in four stages:

1. Estimation of the 2010 baseline population [umbrella model]
2. Projection of population growth to 2030 [umbrella model]

*Technical details of the modeling approach are described more extensively in Carfagna, Cervigni, and Fallavier (2016). Unless otherwise noted, all figures and tables are based on the umbrella model.

3. Modeling of likely effects of resilience interventions targeting:
    a) Livestock systems [livestock model]
    b) Rainfed cropping systems [cropping model]
    c) Irrigation systems [irrigation development model]
4. Consolidation of results [umbrella model]

This appendix provides details of the modeling tools, describes the data used for the simulations, explains key assumptions underlying the analysis, and discusses strengths and weaknesses of the approach.

Geographical coverage

Before considering the modeling tools, it is useful to review the geographical coverage of analysis.

Definition of drylands

For reasons of simplicity and for consistency with widespread common practice, "drylands" are defined on the basis of the Aridity Index (AI). Under this approach, which has been endorsed by the 195 parties to the United Nations Convention to Combat Desertification (UNCCD) and which also is being used by the United Nations Food and Agriculture Organization (FAO), drylands are defined as regions having an AI of 0.65 or less. Drylands are furthermore subdivided into four zones: hyper-arid, arid, semi-arid, and dry subhumid. In some of the analysis (e.g., assessment of the effectiveness of crop farming interventions), the semi-arid zone is additionally divided into a "dry semi-arid zone" and a "wet semi-arid zone." The Aridity Index ranges used to define these zones appear in table A.1.

Country coverage

Because the various analyses required different types of information, the coverage varied depending on data availability (see table A.2).

Table A.1 Aridity Index ranges used to define dryland zones

Aridity Class	Definition	Aridity Index range
1	Hyper-arid	0.00–0.03
2	Hyper-arid	0.03–0.05
3	Arid	0.05–0.20
4	Dry semi-arid	0.20–0.35
5	Wet semi-arid	0.20–0.50
6	Dry subhumid	0.50–0.65

Table A.2 Coverage of the different modeling approaches

Region	Country	Included in		
		Irrigation model	Crop model	Livestock model
East Africa	Djibouti	✓		
	Eritrea	✓		
	Ethiopia	✓	✓	✓
	Kenya	✓	✓	✓
	Somalia	✓		
	South Sudan			
	Sudan	✓		
	Uganda	✓	✓	✓
	Tanzania	✓	✓	
West Africa	Benin	✓	✓	
	Burkina Faso	✓	✓	✓
	Chad	✓	✓	✓
	Côte d'Ivoire	✓	✓	
	Gambia, The	✓	✓	
	Ghana	✓	✓	
	Guinea	✓		
	Guinea-Bissau	✓		
	Liberia	✓		
	Mali	✓	✓	✓
	Mauritania	✓	✓	✓
	Niger	✓	✓	✓
	Nigeria	✓	✓	✓
	Senegal	✓	✓	✓
	Sierra Leone	✓		
	Togo	✓	✓	
Central Africa	Burundi	✓		
	Cameroon	✓		
	Central African Republic	✓		
	Congo, Rep.	✓		
	Congo, Dem. Rep.	✓		
	Equatorial Guinea	✓		
	Gabon	✓		
	Rwanda	✓		
Southern Africa	Angola	✓		
	Botswana	✓		
	Lesotho	✓		
	Madagascar	✓		
	Malawi	✓		
	Mozambique	✓		
	Namibia	✓		
	South Africa	✓		
	Swaziland	✓		
	Zambia	✓		
	Zimbabwe	✓		

The data required for the overall population projections were available for almost all countries in Sub-Saharan Africa.

The data required for the vulnerability analysis were not available for all countries. For East and West Africa, the two subregions on which the analysis concentrates, the coverage was quite limited for East Africa and much more complete for West Africa.

The data required for the resilience analysis similarly were not available for all countries, although the extent of coverage varied depending on the intervention:

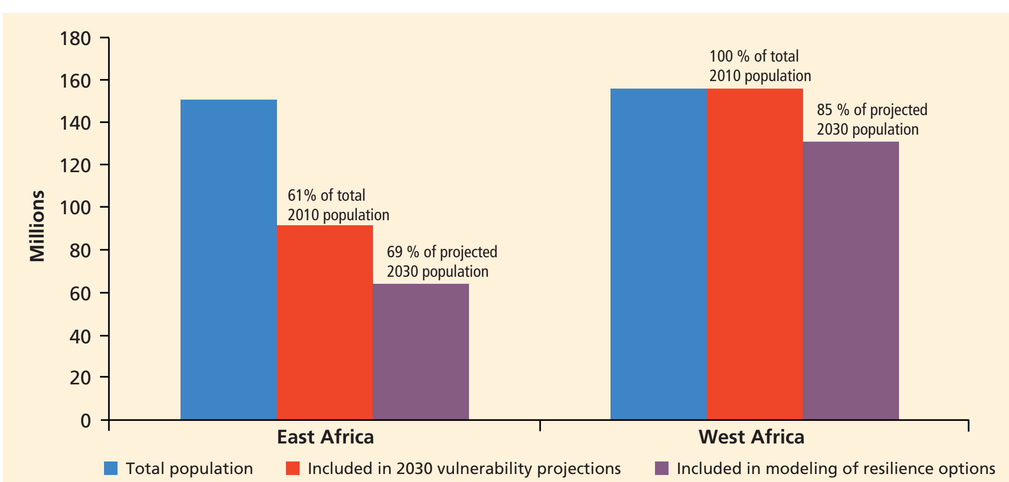
- Irrigation development: Data were available for all countries.
- Rainfed cropping systems: Data were available for most of the countries classified as dryland countries.
- Livestock systems: Data were available only for a subset of dryland countries.

The coverage of the overall resilience modeling analysis is thus defined by the coverage of the livestock systems model, which is the narrowest among the various components. The countries included in the overall resilience analysis account for 85 percent of the projected 2030 population in West Africa and nearly 70 percent of the projected population in East Africa (figure A.1).

Estimation of 2010 baseline population

As discussed at length in the main text of the book, for purposes of the Africa Drylands Study, resilience is determined by three key factors: (1) exposure to droughts and other shocks, (2) sensitivity to droughts and other shocks, and

Figure A.1 Coverage of the umbrella model: Drylands population equivalent of countries included in the analysis



(3) ability to cope with the effects of droughts and other shocks. The estimation of the 2010 baseline population was designed to generate estimates of the numbers of people falling into each of the three categories.

People exposed to droughts and other shocks

These are defined as people living in dryland areas, that is, areas with aridity classes ranging from hyper-arid to dry subhumid. UN population data were spatialized using gridding methods routinely used in the literature (in particular the Global-Urban Mapping Project [GRUMP] dataset developed at the Center for International Earth Science Information Network—CIESIN—at Columbia University).

People sensitive to droughts and other shocks

This group is defined as the share of people dependent on agriculture, estimated using recent IMF (International Monetary Fund) estimates (Fox et al. 2013) of the employment shares of agriculture, and assuming that people below working age depend on agriculture in the same proportion as people above working age. All those working in agriculture are assumed to be equally sensitive to drought shocks. This is admittedly a simplification, since the income share derived from agriculture varies across households. However, data needed to assess consistently across countries the income shares derived from agriculture are not readily available. Survey-based evidence suggests, however, that in dryland areas the share of income coming from farming and livestock is at least 60 percent of the total, so this assumption should not excessively bias the analysis.

People unable to cope with the effects of droughts and other shocks

This group is defined as the proportion of exposed and sensitive people living below the international poverty line of US$1.25 per day. Since separate estimates are rarely available for the rural population only, the national poverty rate was used. The resulting estimates of the number of vulnerable people are probably conservative, because: (1) poverty is usually higher in rural areas than in urban areas, and (2) poverty is usually higher in dryland areas than in nondryland areas.

Recognizing that in drought years, people dependent on agriculture experience income losses, in some of the analyses in this book the number of people unable to cope is estimated using different poverty lines. Based on survey evidence from the United Nations World Food Programme (WFP), it is assumed that households with incomes exceeding the international poverty line of US$1.25 per person per day by 15 percent, 30 percent, and 45 percent become unable to cope in the event of mild, moderate, and severe droughts, respectively. In each case, the corresponding poverty headcount is estimated based on income distribution data obtained from the PovCalnet database.

Using these definitions, the dimensions of vulnerability and resilience in the drylands of Sub-Saharan Africa were estimated in the baseline year of 2010.

Resilience analysis for livestock systems

Five simulation models were used to estimate the likely impacts of resilience-enhancing interventions on feed balances, livestock production, and household income resilience, under different climate scenarios (baseline, mild drought, severe drought).

1. The *BIOGENERATOR* model developed by *Action Contre la Faim* (ACF) uses NDVI (Normalized Difference Vegetation Index) and DMP (Dry Matter Productivity) data collected since 1998 from Spot 4 and 5 (Ham and Filliol 2012). The model was used to estimate spatially referenced usable biomass (that is, biomass that is edible by livestock) in the drylands.
2. The *Global Livestock Environmental Assessment Model—GLEAM* developed by Gerber et al. (2013) calculates at pixel and aggregate level: (1) crop byproducts and usable crop residues; (2) livestock rations for the different types of animals and production systems, assuming animal requirements are first met by high-value feed components (crop byproducts if given, and crop residues), and then by natural vegetation; (3) feed balances at pixel and aggregate level, assuming no mobility at pixel level and full mobility at grazing shed level; and (4) greenhouse gases (GHG) emission intensity.
3. On the basis of the feed rations provided by GLEAM, the *IMPACT model* developed by the International Food Policy Research Institute (IFPRI) was used to calculate the production in drylands of meat and milk and to estimate how production will affect overall supply of and demand for these products in the region.
4. The *CIRAD/MMAGE model* consists of a set of functions for simulating dynamics and production of animal or human populations that are categorized by sex and age class. The CIRAD/MMAGE model was used to calculate the sex/age distribution of the four main ruminant species (cattle, camels, sheep, and goats), the feed requirements in dry matter, and milk and meat production.
5. The *ECO-RUM model* developed by CIRAD under the umbrella of the African Livestock Platform (ALive) is an Excel-supported herd dynamics model based on the earlier ILRI/CIRAD DYNMOD. The ECO-RUM model was used to estimate the socioeconomic effects of changes in the technical parameters of the flock or herd (e.g., return on investments, income, and contribution to food security). The modeling exercise benefitted from livestock distribution data contained in the Gridded Livestock of the World

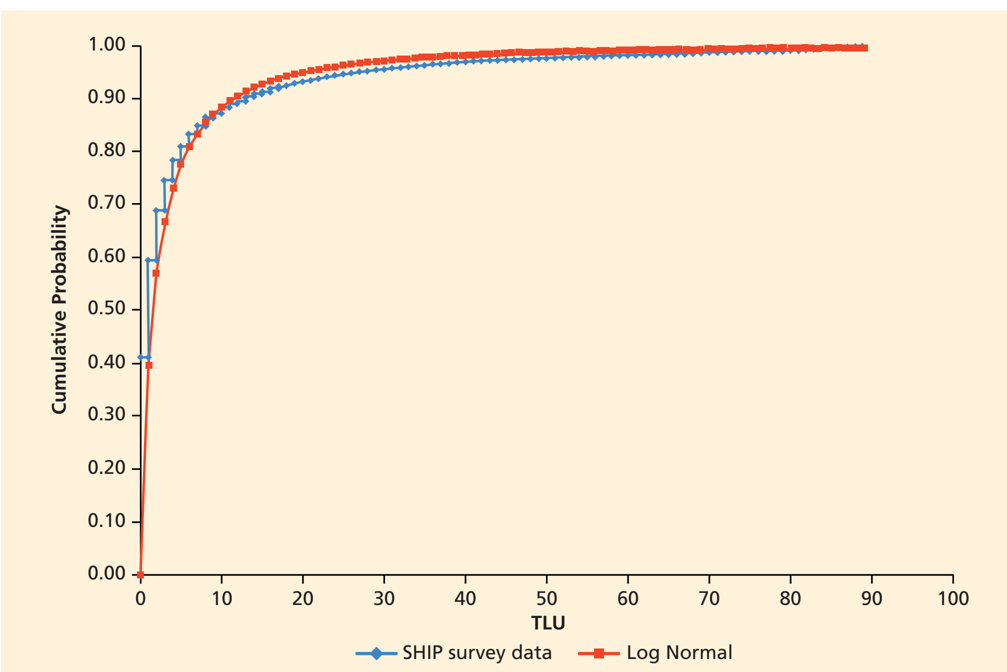
(GLW) database (Wint and Robinson 2007) and its most recent update GLW 2.0 (Robinson et al. 2014). The analysis was informed as well by information and analysis produced by the FAO *livestock supply/demand model* (Robinson and Pozzi 2011). For details, see De Haan (2016).

The results of the models were used as inputs into the final step of the analysis, namely the assessment of the number of households falling into each of three categories: (1) resilient, (2) vulnerable to shocks, and (3) likely to move out of livestock-based livelihoods. These three groups were estimated based on their ownership of livestock, measured in terms of Tropical Livestock Units (TLU). The values of the thresholds used to classify households into one of the three categories were estimated using ECO-RUM, and the corresponding population shares were calculated using a log-normal estimate of the TLU distribution, which approximates quite well (figure A.2) actual TLU distributions emerging from survey data (Survey-based Harmonized Indicators Program [SHIP] database).

The share of households p_t estimated to own less than a certain TLU threshold t is estimated as follows:

$$p_t = \int_0^t f(\tau,\mu,\sigma)d\tau$$

Figure A.2 Burkina Faso: Cumulative distribution of cattle ownership



where $f(\tau, \mu, \sigma)$ is the lognormal probability distribution function; and the two parameters σ and μ are estimated as follows:

$$\sigma = \sqrt{2}\ \Phi^{-1}\left(\frac{G+1}{2}\right)$$

where $\Phi^{-1}\left(\frac{G+1}{2}\right)$ is the inverse of the standard cumulative normal distribution; G is the Gini coefficient, calculated from SHIP survey data (table A.3); and:

$$\mu = ln\ (\bar{t}) - \frac{\sigma^2}{2}$$

where $\bar{t}$ is the average number of TLU/household, calculated by dividing the estimate of the total TLU for the relevant country/production system by the corresponding estimated number of households.

Details on the TLU estimates by country and livestock production systems are contained in the background paper on livestock prepared for this study (De Haan 2016).

The critical TLU thresholds are as follows:

- Below 5 TLU per household: households are assumed to feel pressure to drop out of pastoralism.
- 5–19 TLU per household: households are assumed to continue as pastoralists, but are expected to be vulnerable to drought and other shocks.
- Above 19 TLU per household: households are assumed to be resilient to drought and other shocks.

Table A.3 Gini coefficient of livestock ownership

Country	Survey year	Income Gini	Livestock Gini	Notes
Burkina Faso	2003	39.60	52.07	Survey did not include medium-size livestock
Chad	2011	39.78	73.99	Source: Troisieme Enquete sur la Consommation et le Secteur Informel
Ethiopia	2011	33.60	55.42	
Kenya	2005	47.68	78.13	Excluded TLU > 2,000 (considered outliers)
Mali	2010	33.02	57.81	Estimated based on Income Gini
Mauritania	2008	40.46	66.49	Estimated based on Income Gini
Niger	2007	43.89	67.26	
Nigeria	2004	42.93	76.63	Excluded TLU > 1,500 (considered outliers)
Senegal	2005	39.19	76.05	
Tanzania	2007	37.58	67.32	Survey did not include medium size livestock; excluded TLU >5,000 (outliers)
Uganda	2005	42.62	54.70	Calculation only includes medium-size livestock (figures on large-size livestock appear dubious)

In addition to the Gini coefficient (which is assumed constant throughout the simulation, with the exception of parametric reductions used to simulate the effect of redistribution policies), the other key parameter that determines the number of households below or above the thresholds is the average number of TLU/household.

The average number of TLU/household is estimated by dividing the total number of TLU in the drylands by the total number of households. The numerator in this expression is the maximum number of TLU that the existing biomass can support (on average), estimated through feed balance and herd modeling, based on different levels of access to feed as determined by herd mobility, access to water, insecurity, and urban and crop expansion (further details are provided in De Haan 2016). The denominator in the expression is the number of households estimated to be living in the drylands, based on population growth and projected economic transformation (as explained elsewhere in the book).

The effect of the livestock interventions on vulnerability (and thus indirectly on the number of drought-affected people) is captured by running the model with different values of the TLU resilience threshold (table A.4), estimated through ECO-RUM herd modeling. Lower TLU thresholds imply that for a given distribution of livestock assets, more households will be above the threshold, and fewer households will be below the threshold, compared to the business as usual/no intervention scenario.

Interventions that result in the improvement of animal health reduce the mortality rate and increase the number of animals that can be sold, thereby reducing the number of TLU needed to reach a certain level of income (in particular, the international poverty line of US$1.25/day). Similarly, interventions that promote the sale of animals at a younger age for fattening in high rainfall areas increase the price received per animal and reduce overall mortality, similarly reducing the number of TLU needed to reach a certain income level.

Resilience analysis for rainfed cropping systems

Similarly to the case of livestock, potential impacts on resilience of interventions targeting rainfed cropping systems are modeled. The analysis is carried out in two stages. In the first stage the objective is to estimate the potential impact of

Table A.4 Tropical Livestock Units (TLU) required to attain resilience

Livestock system	Business as usual			Health and early offtake		
	Baseline weather	Mild drought	Severe drought	Baseline weather	Mild drought	Severe drought
Pastoral	21.1	23.3	24.8	15.7	17.4	18.7
Agro-pastoral	12.9	14.2	15.3	7.4	8.3	8.5

the adoption of best-bet crop farming technologies on the yields of crops grown by agro-pastoralist and crop farming households. In the second stage the objective is to estimate how these yield changes are likely to translate into income changes and how these income changes impact agro-pastoralist and crop farming households.

Modeling impacts of best-bet technologies on crop yields

The potential impact of the adoption of best-bet crop farming technologies on the yields of crops grown by agro-pastoralist and crop farming households is estimated using IFPRI's grid-based crop modeling platform. Because it would have been impractical to model the full range of crops grown in the drylands, the analysis is carried out using the dominant cereal crop grown in any given location, identified with the help of IFPRI's Spatial Production Allocation Model 2005 (You et al. 2014) in 2,294 grid cells distributed across 16 countries. The dominant rainfed crops are millet and sorghum in arid and dry semi-arid zones, and maize in wet, semi-arid, and dry subhumid zones.

The crop yield simulations were carried out using three crop models that are part of the (Decision Support System for Agrotechnology Transfer) DSSAT Cropping System Model v4.5 (CERES-Maize, CERES-Sorghum, and CERES-Millet). Yields were simulated at the level of each grid cell over a 25-year period. Using the assumption that weather in the drylands during the next 25 years will not be significantly different from weather experienced during the past 25 years, daily weather data 1984–2008 were used as input (Ruane, Goldberg, and Chryssanthacopoulos 2015). Soil properties in each grid cell were represented using IFPRI's HC27 Generic Soil Profiles Database (Koo and Dimes 2013). Planting date windows for the three representative crops were synchronized with the cropping calendar of the ARV model (described below). A representative variety of each crop was selected and used across the region. Additional details on the modeling platform setup are available in Rosegrant et al. (2014).

Best-bet crop farming technologies

The DSSAT framework was used to assess the potential impact on yields likely to result from the adoption of five best-bet crop farming technologies: (1) drought-tolerant varieties, (2) heat-tolerant varieties, (3) additional fertilizer, (4) agroforestry practices, and (5) water harvesting techniques. The potential impact on yields was modeled separately for each technology, as well as for several combinations of technologies expected to have synergies (e.g., varieties with drought tolerance and heat tolerance, drought- or heat-tolerant varieties grown with additional fertilizer, and drought- or heat-tolerant varieties grown in combination with agroforestry).

1. Drought-tolerant varieties

To simulate the likely impacts of adoption of drought-tolerant varieties, which are known to have superior rooting ability in the presence of low levels of soil moisture, the model was adjusted by increasing the soil root growth factor parameter in each soil layer. Enhanced water extraction capability was also simulated by lowering the lower limit parameter in the soil profile. In the case of maize, the sensitivity was reduced by the anthesis-silking interval (ASI) to soil moisture content.

2. Heat-tolerant varieties

The species characteristics definition for each of the three indicator crops includes parameters regarding the response of plant growth and grain filling rates to temperature. In the case of maize, for example, the CERES-Maize model defines the optimum and maximum temperatures for grain filling as 27°C and 35°C, respectively. To mimic the ability of heat-tolerant varieties to continue growing and filling grain at higher temperatures, the values of these two parameters were increased by 2°C for the heat-tolerance simulations.

3. Additional fertilizer

The baseline, no-intervention scenario includes an inorganic nitrogen fertilizer application rate that is specific to each region, input system, and crop, which was obtained by calibration of simulated raw yields to FAOSTAT-reported country-level yields. For the best-bet fertilizer intervention, the baseline fertilizer application rate was increased by 50 percent.

4. Agroforestry

To simulate the improvements in soil fertility expected to result from decomposing leaves from *Faidherbia* trees planted in the same field as the indicator crops, for each cropping cycle an additional input of organic soil amendments was implemented 10 days before planting. The trees were assumed to be 20 years old in year 1, so that the amount of organic matter contributed throughout the simulation period remains constant. Each tree is assumed to produce 100 kg of leaves, of which 4.3 percent is nitrogen. These values are taken from scientific studies in West Africa. Two tree density values were simulated (5 trees per hectare and 10 trees per hectare), to test the sensitivity of crop yields to tree density. Canopy coverage, which determines the area within each field that actually benefits from the decomposition of tree-contributed organic matter, is assumed to be 10 percent and 20 percent for tree densities of 5 trees per hectare and 10 trees per hectare, respectively. These densities have been observed in many locations in the semi-arid drylands where farmer-managed natural regeneration (FMNR) is practiced. It is useful to recall, however, that while *Faidherbia* is distributed throughout the drylands of Africa, it will not emerge through regeneration in all locations.

5. Water harvesting

To simulate the potential effects of harvesting runoff and storing it *in situ* for use in supplementary irrigation, a two-stage approach was implemented. The model was first run without any water management practices, and the output was analyzed to identify periods during the growing season when yields are constrained by lack of water. These periods represent opportunities for implementing improved water harvesting and supplementary irrigation practices. The simulation results were also used to determine when supplementary irrigation can have the largest impact on yields (e.g., immediately after germination and before flowering), and also to estimate how much of the harvested water would be available from the *in situ* storage. The model was then run again including harvested runoff water in the form of supplementary irrigation.

Modeling impacts of crop yield gains on vulnerability

In the second stage of the analysis, the objective is to estimate how changes in the mean level and distribution of yields associated with adoption of the best-bet technologies are likely to translate into income changes and how these income changes could impact agro-pastoralist and crop farming households. This analysis was carried out using the Africa RiskView (ARV) model developed by the African Risk Capacity.

The ARV model uses static drought vulnerability profiles of the population in each area unit to measure the impacts of drought under different scenarios. More precisely, the ARV model estimates the proportion of the population that is likely to be affected by drought in the presence of drought of different magnitudes. The frequency, intensity, and duration of drought is measured in terms of deviations of a rainfall-based drought index (WRSI) below a defined benchmark multiplied by a scaling factor that translates negative WRSI deviations into potential household income deviations.

Noteworthy features of the ARV model include the following:

- Three different threshold WRSI deviations allow the definition of three levels of vulnerability: (1) vulnerability to mild drought, (2) vulnerability to medium drought, and (3) vulnerability to severe drought. For each analysis unit, the overall vulnerability profile is calculated based on the percentages of the population vulnerable to each of the three levels of droughts.
- The scaling factor used determines the impact of WRSI deviation on crop yields, which in turn translates into impacts on agricultural income of households.
- The vulnerability profiles are defined based on household survey data, which reveal the extent to which households in a specific area unit are both (1) exposed to drought (defined by their percentage of total income generated by agriculture-related activities) and (2) able (or not) to absorb and

recover from income shocks (defined by their ranking on a wealth scale compared to the national poverty rate).

Using the outputs of the DSSAT crop modeling simulations (described in the previous section) as an input instead of WRSI, the ARV model can simulate the impact of drought without and with the best-bet technologies. To avoid potential distortions associated with using yield estimates instead of WRSI values, it is assumed that the differences in crop yields attributable to adoption of the best-bet technologies translate into equivalent differences in agricultural income (in the ARV model, this is tantamount to setting the scaling factor to a value of 1:1). The threshold deviations from WRSI that define mild, medium, and severe drought are therefore adjusted accordingly for the use of DSSAT-based input data.

Specific vulnerability profiles at Admin1 level (the first level of sub-national jurisdiction) are created for 2010 and 2030. The 2030 profiles are based on a number of assumptions about demographic increases, economic growth, and structural transformation (described above) that determine how the number of people below the poverty line and the percentage of people employed in agriculture will change by 2030. Within each Admin 1 level unit (that is, the first sub-national level of administrative jurisdiction), the vulnerability profiles can be broken down further by aridity zone. Vulnerability profiles for 2010 and 2030 under the medium fertility scenario are available for the majority of East and West African countries. As an example, table A.5 shows for Mauritania the vulnerability profiles for 2010 and 2030 for the three drought cases.

Table A.5 Mauritania: Drought Vulnerability Profile for mild, medium, and severe drought (population, millions)

Region	Aridity	Mild drought		Moderate drought		Severe drought	
		2010	2030	2010	2030	2010	2030
Assaba	Arid	0.101	0.141	0.122	0.170	0.140	0.196
Brakna	Arid	0.094	0.132	0.113	0.159	0.131	0.183
Gorgol	Arid	0.095	0.134	0.115	0.161	0.133	0.186
Gorgol	Dry semi-arid	0.001	0.001	0.001	0.001	0.001	0.001
Guidimaka	Arid	0.031	0.044	0.038	0.053	0.044	0.061
Guidimaka	Dry semi-arid	0.043	0.060	0.052	0.073	0.060	0.084
Hodh Ech Chargui	Arid	0.115	0.161	0.139	0.195	0.160	0.224
Hodh El Gharbi	Arid	0.087	0.123	0.106	0.148	0.122	0.171
Tagant	Arid	0.021	0.029	0.025	0.035	0.029	0.041
Trarza	Arid	0.092	0.129	0.111	0.155	0.128	0.179
Total		**0.680**	**0.953**	**0.821**	**1.150**	**0.947**	**1.327**

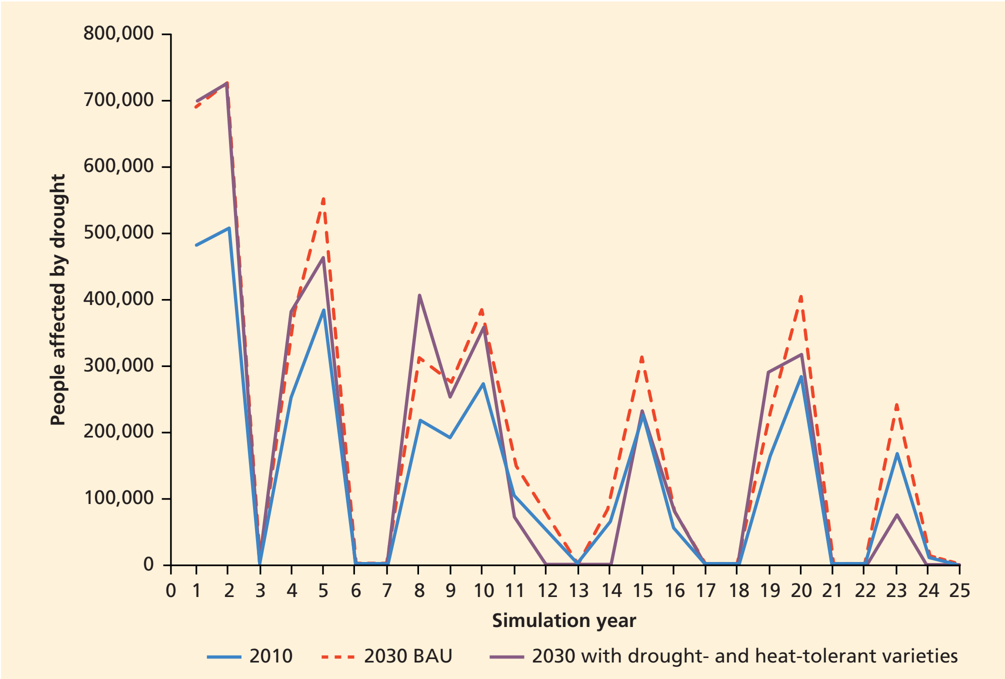
The definition of mild, medium, and severe drought is kept the same in both the 2010 and 2030 profiles. Furthermore, since the poverty line of US$1.25/day is used in both the 2010 and 2030 vulnerability profile definitions, a comparison of these two baseline profiles (BAU) gives an indication of how economic growth and structural transformation are likely to impact the proportion of the population vulnerable to drought as defined by the ARV model. For example, in Mauritania, even though the share of the poor in total population is projected to decline, the absolute number of people vulnerable to drought will actually increase by some 40 percent.

It is important to note that the definitions of drought associated with the vulnerability profiles—mild, medium, and severe—are not linked to return periods of drought, nor necessarily to the risk of drought occurring in a particular Admin 1 unit. Rather, the terms are related to levels of household income loss resulting from drought events. For this reason, adoption in an Admin 1 level unit of one of the best-bet crop farming technologies does not change the vulnerability profile prevailing in that unit. Rather, the changes in the mean level and distribution of crop yields registered in that unit following the adoption of the technology *affects the impact on incomes* of a mild, medium, or severe drought, and therefore affects the probability of hitting the drought-specific threshold. To capture the impact in 2030 of adopting one or more of the best-bet technologies, it is necessary to maintain the definition of drought in the model (in terms of the benchmark and thresholds) and then to calculate the changes in expected number of people affected by drought, given likely yield projections for the various intervention and non-intervention scenarios.

For example, consider first the non-intervention scenarios and the medium fertility scenario. Assume that the rainfall and the resulting crop yields that can occur in an area in 2010 and 2030 come from the same distribution, that is, that there is no change in climate. The DSSAT model can be used to generate yields for 25 years for each Admin 1 level/aridity zone unit. Assume these 25 values represent a sample from a yield distribution for both 2010 and 2030. These 25 yield values can be imposed on the 2010 and 2030 vulnerability profiles to estimate possible drought-affected populations in those scenarios. Figure A.3 shows the estimated number of drought-affected people in Mauritania using the 25 yield values.[1]

To estimate the impacts of the best-bet crop farming technologies on vulnerable populations, the DSSAT model was used to simulate how the various technologies impact the mean level and distribution of yields. Distributions of the drought-affected population estimated using the yield values from the 25 simulation years for each best-bet technology can be compared to distributions of drought-affected populations estimated under the baseline scenario in which yields do not benefit from the adoption of any of the best-bet technologies. The

Figure A.3 ARV estimates of drought-affected people in Mauritania expected for each of 25 simulated yield years



differences show the impact of each technology on the drought-affected population, or in other words, on household resilience.

Figure A.3 shows, again for the case of Mauritania, the effects of adopting one of the best-bet interventions considered in the analysis (specifically, the adoption of a crop variety that is both drought-tolerant and heat-tolerant). Compared to the 2030 no-intervention scenario (BAU), the number of drought-affected people declines in many years; in some years, the result is only to slow down the increase in the number of drought-affected people, while in other years the number of drought-affected people actually falls below the 2010 baseline. Overall, adopting the drought- and heat-tolerant variety leads to an 11 percent decrease in the number of drought-affected people. This example shows the benefit of a single intervention adopted in all polygons where it is effective. In the model, benefits are maximized when the entire set of interventions is considered, and in each polygon the intervention is selected that yields the largest reduction in the number of drought-affected people. The results presented in the main text of the book are based on the latter approach.

Irrigation resilience analysis

The final intervention modeled is irrigation development. The assessment of the potential impacts of irrigation development on the population living in drylands builds on the same drought characterization method used for the analysis of impacts of interventions in rainfed cropping systems (see the previous appendix section, Resilience analysis for rainfed cropping systems), combined with work done by IFPRI on irrigation investment potential in African drylands (Xie et al. 2015). In the IFPRI work, the potential for expanding large-scale irrigation (LSI) and small-scale irrigation (SSI) in dryland areas of Sub-Saharan Africa by 2030 are modeled separately. (See box A.1 for details on the SSI modeling exercise.)

It is important to note that the area identified as having irrigation investment potential should be interpreted as "physical area equipped with irrigation infrastructure," since the water balance figures used to make the projections are long-term averages. In drought years when water becomes scarce, irrigation can not be delivered everywhere, leaving part of the area equipped with irrigation infrastructure unused. This becomes important in the latter stages of the analysis, when the impacts of irrigation on drought-affected people are estimated in the face of weather variability and climate change.

The impact of irrigation development on reducing vulnerability and increasing resilience in the drylands was assessed using a two-step procedure. The first step involved estimating the area that is actually irrigated, taking into account climatic variability. The second step was to estimate, based on the results of the first step, the population that can be considered no longer affected by drought for each Admin 1 level/aridity zone unit.

The key steps and assumptions used in the analysis are shown below:

SSI can use either surface water or groundwater. Groundwater acts as a buffer against the impact of drought. The abundance of groundwater storage and accessibility to groundwater in African drylands is evaluated through geographic information system (GIS) analysis using groundwater depth and storage data developed by British Geological Survey (table A.6).

Table A.6 Aquifer classification in British Geological Survey groundwater data

Class	1	2	3	4	5	6
Depth to groundwater (meters)	0–7	7–25	25–50	50–100	100–250	>250
Groundwater storage (millimeters)	0	<1,000	1,000–10,000	10,000–25,000	25,000–50,000	>50,000

BOX A.1

Estimating the expansion potential for small-scale irrigation (SSI)

The method used to assess SSI development potential begins with an irrigation suitability analysis. Within each pixel, various criteria are used to score the environmental suitability of each pixel, including topography (slope), groundwater accessibility, distance to perennial surface water, proximity to existing irrigation, and market access.

For the ex ante suitability analysis, the criteria parameters are divided into three classes, and linear interpolation is used within the classes to calculate the scores. Such a classification is similar to a stepwise function, which provides flexibility to adjust the threshold values after consulting with experts and stakeholders. The overall rating of the irrigation suitability is the average of all scores for all applicable criteria. Since groundwater and surface water provide the same water resource to irrigation, overall suitability is calculated as the larger of the two scores. In other words:

$$S = \frac{S1 + max\ (S2,S3) + S4 + S5}{4}$$

where: S = irrigation suitability score, $S1$ = score for slope, $S2$ = score for surface water access, $S3$ = score for ground water access, $S4$ = score for ground distance to existing LSI, and $S5$ = score for market access.

The ex ante suitability analysis is done on a 0.5 x 0.5 km grid. The suitability score is then used as a percent of the pixel suitable for irrigation. In other words, the area with SSI development potential in a pixel is calculated as:

$$A_{irr,exante} = A_{pixel}\ x\ \frac{S}{100}$$

where: $A_{irr,exante}$ = area suitable for irrigation development (ha), and A_{pixel} = pixel size (= 25 ha).

Next, the expansion of SSI is simulated. The starting point for the analysis is the current cropping pattern. Data on area harvested, production, and yield under irrigated and rainfed systems on a grid of approximately 10 x 10 km were obtained from the IFPRI Spatial Production Allocation Model (SPAM) database (for details, see You, Wood, and Wood-Sichra 2009). Prior to the simulation, the results of the ex ante suitability analysis were incorporated into the SPAM grid. The suitability score for each SPAM pixel was calculated as the average of the pixels in the coarser grid used for the suitability analysis, and the total area within each SPAM pixel deemed suitable for irrigation was calculated as the sum of the areas within the pixels used for the suitability analysis.

To account for the expansion in cultivated area and changes in cropping patterns that may be caused by irrigation development, the following key assumptions were made:

(continued next page)

Box A.1 *(continued)*

- Irrigation can occur during both the wet and dry seasons (both seasons are recognized in the analysis). Based on empirical evidence from past studies (Xie et al. 2015), the following 10 crops can be irrigated during the rainy season: (1) wheat, (2) rice, (3) maize, (4) sorghum, (5) millet, (6) potatoes, (7) sweet potatoes, (8) groundnuts, (9) sugarcane, and (10) vegetables. Wheat, maize, rice, and vegetables are assumed to be the dry-season irrigated crops.
- During the irrigation expansion, (1) the currently existing rainfed cultivated area in a country will first be converted to irrigated area before new area is brought into cultivation/irrigation; (2) irrigation will expand according to the overall rating of the irrigation suitability, that is, irrigation development first takes place in the pixels with the highest suitability scores and is followed by development in pixels with the second highest ranking; and (3) irrigation expansion is constrained by water availability and national-level food demand for irrigated crops.

The detailed simulation algorithm is described in Xie et al. (2015). It is assumed that the area cultivated for a given crop *c* on irrigated land, either converted from existing rainfed land or expanded from non-farming area, is proportional to the profitability of cultivating that crop.

$$A_c^i = A_{total} \; x \; \frac{profit_c}{\Sigma_c \; profit_c}$$

where: A_{total} = total irrigated area (ha), and $profit_c$ = annual profit farmers receive from cultivating crop *c* (\$/ha).

Profit is calculated as follows:

$$Profit_c = Y_c^i \bullet P_c \bullet ProfitRatio_c$$

where: Y_c^i = yield of crop under irrigation (ton/ha), derived from FAO's Global Agro-Ecological Zones (GAEZ) database (http://www.fao.org/nr/gaez/en/) under an assumption that irrigated yields would be 50 percent of the GAEZ potential yields for the 2050 analysis; for 2030 it is assumed that 80 percent of the 2050 yields can be achieved; P_c = producer price of crop *c* (\$/ton), derived from the FAO PriceSTAT database, $ProfitRatio_c$ = profit margin (0 ~1) of crop *c* (PriceSTAT appendix table 1.3).

To calculate the internal rate of return (IRR), first annual net revenues from the irrigation expansion are calculated without taking into consideration irrigation costs.

The net revenue in the rainy season on converted rainfed land in a SPAM pixel (\$/yr) is calculated as:

$$NetRevenue_{wet} = \Sigma_c \, Y_c^i \bullet P_c \bullet ProfitRatio_c \bullet A_c^i - \Sigma_c \, Y_c^r \bullet P_c \bullet ProfitRatio_c \bullet A$$

where: Y_c^r = rainfed yield of crop *c* (ton/ha) and A_c^r = rainfed area of crop *c* in the pixel (ha).

The net revenue in the rainy season on newly cultivated, irrigated land in a SPAM pixel (\$/yr) is calculated as:

(continued next page)

Box A.1 *(continued)*

$$NetRevenue_{wet} = \Sigma_c\, Y_c^i \bullet P_c \bullet ProfitRatio_c \bullet A_c^i$$

The net revenue on converted rainfed land or newly cultivated irrigated land in dry season is calculated as:

$$NetRevenue_{dry} = \Sigma_c\, Y_c^i \bullet P_c \bullet ProfitRatio_c \bullet A_c^i$$

The net revenue per unit area (without consideration of irrigation costs) is calculated as:

$$NetRevenue\_per\_ha = \frac{NetRevenue_{wet} + NetRevenue_{dry}}{\Sigma_c A_c^i}$$

With the calculated net revenue per unit area, the cash flow in year t required for the IRR calculation is calculated as:

$$NetRevenue\_per\_ha * B_t - A_t * IRR\_Cost_c * C_t - IRR\_COST_O$$

where: IRR_Cost_c (\$/ha) = the annualized capital investment cost for SSI expansion, IRR_Cost_c = annual SSI operating costs (\$/ha), and B_t and C_t = factors used to amortize capital investment and revenue in the calculation of cash flow associated with irrigation infrastructure development. The calculation assumes a five-year investment cycle and a 50-year investment horizon.

It is assumed that SSI in areas with groundwater depth below 25 meters (m) and storage greater than 10,000 millimeters (mm) is primarily groundwater-based and not influenced by drought.

The variation of actual area under surface water-based SSI and LSI is modeled as a function of the drought index I.

$$A_i = A_O \bullet e^{-\alpha I}$$

where A_i is actual area of irrigation in year i; A_O is physical area equipped with irrigation; I is the drought index. Its value may vary between 0 and 1. $A_i = A_O$ if $I = 0$; and in a drought year, $I > 0$ and $A_i < A0$, α is a parameter controlling the contraction rate of irrigation area under drought. The higher the value of α, the larger the reduction in irrigation area in drought years.

The drought index is calculated as follows:

$$I = \frac{Y_{benchmark} - Y_i}{Y_{benchmark}} \quad if = Y_{benchmark} > Y_i;\ otherwise\ I{=}0$$

where:

$Y_{benchmark}$ is the benchmark yield defined in the ARV model, and Y_i is the crop yield in a given year t. Given that large reservoirs likely have multi-year storage capacity, LSI tends to be more resilient to drought than surface-water-based SSI.

Therefore, a smaller value of α is specified for LSI in the simulation. α is set to 0.5 for LSI and 1.0 for SSI.

The simulation of "actual" LSI and SSI irrigated areas is conducted at 5-arc minute resolution (approximately 10 km by 10 km). The calculated pixel-wise values of "actual" areas of irrigation are aggregated to the Admin 1 level/aridity zone unit. The number of poor people in each unit is calculated under the assumption that "0.5 hectares of irrigated land supports one household (HH) comprising 5 people" and accordingly vulnerability shares are developed from the ARV model as:

$$Pop_i = A_i \ x \ 10 \ x \ \eta$$

where Pop_i is population in a unit and in year i is rendered resilient to drought through irrigation, A_i is actual area of irrigation in the unit, and year i, η is the vulnerability share of population obtained from the ARV model. A key assumption underlying the analysis is that where there is potential for irrigation development, vulnerable people will be able to take advantage of the opportunity and equip their farm with SSI equipment, regardless of their income level. In other words, the ability to take advantage of opportunities to invest in irrigation is assumed to be the same for every household located in areas with irrigation development potential, irrespective of their income level.

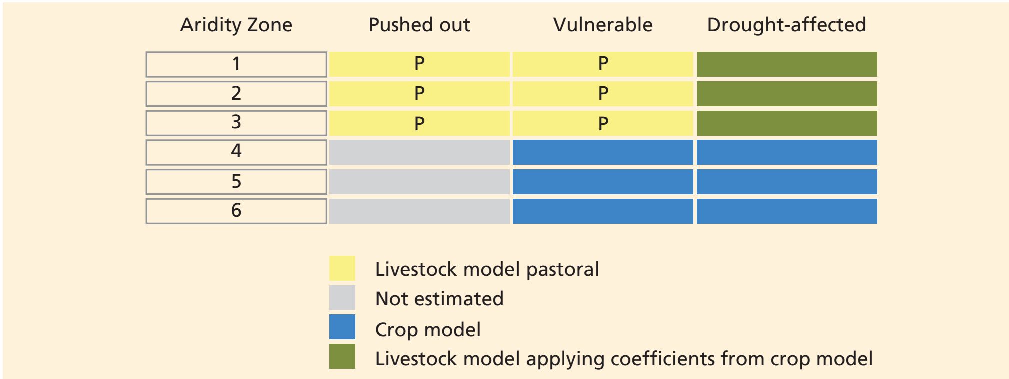
Consolidating the results of the resilience analysis

Estimated reductions in the numbers of drought-affected people likely to result from interventions in livestock systems and rainfed cropping systems, as well as from investments in irrigation, are consolidated in a set of figures presented in the book.

Key elements of the consolidation process include the following:

- The livestock model was used to generate estimates of the number of vulnerable people (without and with the interventions) in hyper-arid and arid zones only (aridity classes 1 to 3, see figure A.4), using the model's parameters for pastoral livelihoods.
- Results expressed in terms of number of households were converted into numbers of people by assuming an average household size of six people.
- The number of drought-affected people was estimated applying country-specific drought incidence factors (average number of drought-affected people as percentage of vulnerable people) obtained from the crop model. This is justified on account of the likely significant correlation between drought impacts on the staple crops modeled (maize, millet, sorghum) and impacts on the grasses found in rangelands.

Figure A.4 Schematic of livelihood modeling



- The livestock model estimates of the number of households below the critical threshold of 5 TLU/household (figure A.4) were used to calculate the number of people who are likely to transition from pastoralism to farming; these households were then added to the number of vulnerable people engaged in crop farming. Country-level estimates of the number of people who are likely to transition from pastoralism to farming were distributed across the country's polygons (intersection of administrative units and aridity zones) using each polygon's share in the country's total number of vulnerable people.
- The number of drought-affected people engaged in crop farming in aridity classes 4 to 6 (including both the original crop farmers as well as the people who are likely to transition from pastoralism to farming) was estimated using the crop model.

The approach used in this book does not consider the significant scope for implementing livestock-related interventions in agro-pastoral systems found in semi-arid and dry subhumid zones. For this reason, while the modeling results indicate the order of magnitude of the likely resilience benefits of the different interventions, they represent conservative lower bound estimates of the full potential.

Cost estimates

Livestock

Cost estimates for the analysis of livestock systems are based on cost projections from five recently launched internationally funded projects dealing with pastoral areas.[2] These data were complemented with data obtained through a review of the literature. Table A.7 provides a summary of the cost per pastoral/agro-pastoral person associated with these projects.

Table A.7 Average cost/person/year (weighted according to number of beneficiaries) of the main interventions in five dryland livestock development projects

Intervention	Average cost/person/year (US$)	Number of projects	Range (US$)
Health improvement	3.95	3	3.37–20.12
Market improvement (early offtake of bulls)	6.00	3	3.67–8.33
Early warning systems	3.72	2	1.79–2.09
Social services, etc.	5.30	2	2.39–5.82

The range of values is significant, particularly for health improvement. However, the average is in line with the estimates of the World Organisation for Animal Health (OIE)-sponsored study (CIVIC Consulting 2009) for Uganda.

For development decision making, it is important to know the distribution between technology adoption-related and non-adoption-related costs, as well as between investment and recurrent costs. The assumptions used are based on the projects analyzed and the authors' experience; they are provided in table A.8.

Table A.8 Assumptions about the allocation of adoption- and non-adoption-related costs and of investments and recurrent costs for animal health and early offtake interventions

Item	Allocation
Animal health non-adoption-related	Of total health improvement budget, 20% in investments and 25% in recurrent costs
Animal health adoption-related	Of total health improvement budget, 25% in investment and 30% in recurrent costs
Animal health improvement adoption-related by livestock system	10% higher/person (higher delivery costs) in pastoral systems
Early offtake (market integration)	Of total budget, 70% in investment and 30% in recurrent costs (high capital investment needed in infrastructure such as transport, processing facilities)
Early offtake non-adoption-related costs	Nil, because of its currently nascent character
Adoption rate	70% for pastoral and 80% for agro-pastoral households for health improvement and 60% and 70%, respectively, for early offtake
Public and private sector contribution	Public sector: 80% for cross-cutting costs, 60% for adoption costs in animal health improvement, and 20% for early offtake; the remainder belongs in the private sector

In aggregate, these figures seem high, at a total of about US$10 billion over the 20-year period (table A.9) or about US$500 million/year (about US$200 million/year for the public sector.

They look more reasonable when calculated per beneficiary (number of people made resilient), as shown in figure A.5.

Table A.9 Summary of costs (2011–14 prices, US$ billion) of health and early offtake interventions and their distribution between the public and private sectors (2011–30)

	Cross-cutting costs	Adoption costs animal health	Early offtake costs	Total
Public sector	1.14	1.69	1.18	4.01
Private sector	0.29	1.13	4.71	6.12
Total	1.43	2.82	5.88	10.14

Figure A.5 shows that with the exception of Niger, the costs per person made resilient are significantly below the US$100–135 normally calculated for food aid. As expected, the annual cost per person made resilient is higher in pastoral areas. In general, the costs in East Africa seem to be lower than in the Sahel. At an average cost of US$27 per person per year, they are half the US$65 per person per year estimated by Venton et al. (2012).[3]

Rainfed crops

The cost of adopting the rainfed cropping technologies includes public costs borne by the public sector during an initial period when a technology is first being introduced (e.g., costs associated with extension campaigns, demonstrations, free samples; see table A.10), as well as private costs borne by the adopting farmers themselves (e.g., the cost of purchasing seed or fertilizer, or the cost of performing additional operations such as planting fertilizer trees or building water harvesting structures).

Figure A.5 Estimated unit cost (US$/person made resilient/year, expressed on a log scale) under baseline climate and health and early offtake scenarios

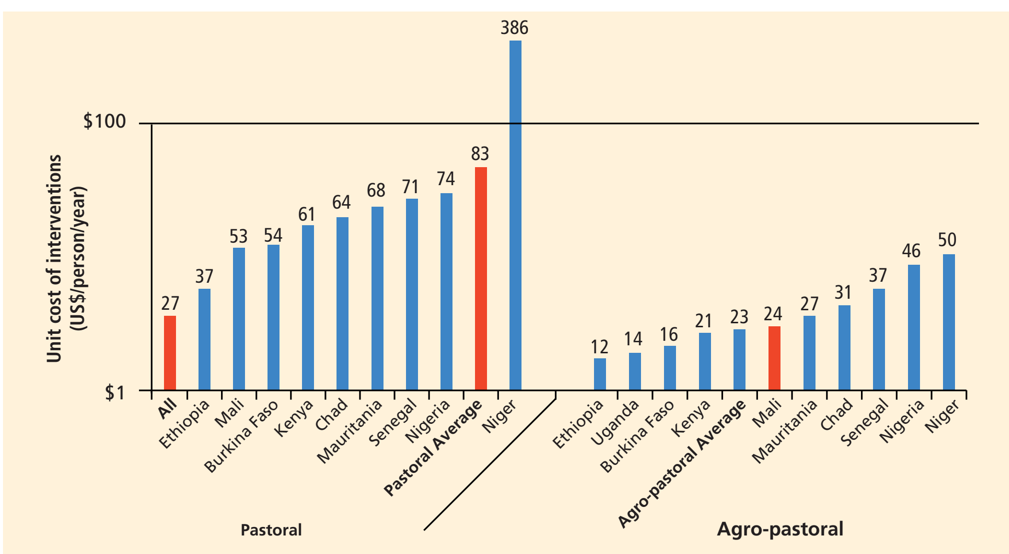


Table A.10 Public costs of technology transfer (US$/hectare)

Description	Millet	Sorghum	Maize
1: Drought tolerance	1.25	1.35	1.50
2: Heat tolerance	1.25	1.35	1.50
3: More fertilizer	10.00	10.00	10.00
4_5: Agroforestry 5 trees/ha	45.00	45.00	45.00
4_10: Agroforestry 10 trees/ha	45.00	45.00	45.00
5: Water harvesting	20.00	20.00	20.00

Private costs (that is, costs borne by farmers themselves) were included in the analysis by adjusting downward the yield gain associated with adoption of the technology by a discount factor estimated to represent the cost of adopting the technology. To reflect the fact that farm households will use part of their income to purchase the inputs required for adopting the technology (e.g., labor, seed, fertilizer), costs were expressed in terms of the crop equivalent of purchasing the required inputs, with production valued at country- and crop-specific farm-gate prices calculated as averages of the corresponding FAOSTAT values over the period 2000–12.

The cost (estimated on the basis of the literature and expert judgment) varied by technology (table A.11). In some cases it was modest (e.g., adoption of drought-tolerant and heat-tolerant varieties, adoption of FMNR), whereas in other cases it was more substantial (e.g., additional fertilizer, water harvesting). In recognition that technology adoption costs may be borne by the farmer or by the state (in the form of subsidies), sensitivity analysis was carried out to explore the impacts on adoption incentives of differing levels of private costs.

To reflect the fact that the best-bet crop farming technologies will not all be profitable in every location, a switch was built into the model to determine which technology is adopted in any given polygon. The switch works as follows: if adoption of a given best-bet technology has the effect of reducing the number of drought-affected people, that technology is deemed effective and retained,

Table A.11 Private costs of technology adoption (US$/hectare)

Description	Millet	Sorghum	Maize
1: Drought tolerance	3	3	15
2: Heat tolerance	3	3	15
3: More fertilizer	30	30	30
4_5: Agroforestry 5 trees/ha	7	7	7
4_10: Agroforestry 10 trees/ha	9	9	9
5: Water harvesting	45	45	45

but if adoption of that technology has the effect of increasing the number of drought-affected people, the technology is deemed ineffective and discarded.

In addition, because synergies resulting from the simultaneous adoption of multiple best-bet technologies are not captured well by the DSSAT model, the analysis used the simplifying assumption that only the most effective technology is adopted in a given location. Because simultaneous adoption of multiple technologies would certainly result in additional benefits (in terms of yield increases and income gains), the resilience-enhancing impacts of adoption of improved rainfed cropping technologies should be considered conservative.

Irrigation

Given the considerable uncertainty and wide range of irrigation technology and expansion costs, three sets of cost assumptions were considered in the analysis of irrigation development, ranging from US$8,000–US$30,000 per hectare for LSI, and from US$3,000–US$6,000 per hectare for SSI (table A.12). The medium-cost assumptions were used for the baseline scenario.

Table A.12 Irrigation development unit cost assumptions (US$/hectare)

	Low		Medium		High	
	Capital	Operation and maintenance	Capital	Operation and maintenance	Capital	Operation and maintenance
LSI	8,000	800	12,000	1,200	30,000	3,000
SSI	3,000	100	4,500	125	6,000	150

Source: Xie et al. 2015.

Notes

1. The national population affected is the sum of the populations affected in each Admin 1/aridity zone.
2. The Ethiopia-Drought Resilience & Sustainable Livelihood Program in the Horn of Africa (PHASE I), funded by the African Development Bank (US$48.5 million, 2012); the International Fund for Agricultural Development (IFAD)- and World Bank-funded Regional Pastoral Livelihoods Resilience Project for Kenya and Uganda (US$132 million, 2014); the World Bank-funded Regional Sahel Pastoralism Support Project (US$250 million, under preparation); the World Bank/IFAD-funded Ethiopia Pastoral Community Development Project–Phase II (US$133 million, 2013); and the IFAD-funded Sudan Livestock Marketing and Resilience Program (US$119 million, under preparation).
3. US$54/person/year for Kenya and US$77/person/year for Ethiopia. No data are available for the Sahel.

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