iDMC internal displacement monitoring centre

THEMATIC SERIES

The ripple effect: economic impacts of internal displacement

This thematic series focuses on measuring the effects of internal displacement on the economic potential of IDPs, host communities and societies as a whole

BRIDGING A DATA GAP

Estimating the cost of internal displacement in sub-Saharan Africa with modelled projections

DECEMBER 2019

www.internal-displacement.org

INTRODUCTION

IDMC published its first estimates of the economic impact of internal displacement in eight countries in February 2019, using secondary data analysis to measure the cost of meeting the needs of internally displaced people (IDPs) in terms of health, education, security, housing and livelihoods.[1] Country-specific data was mostly found in Humanitarian Response Plans (HRPs) and other reports, which meant the estimates were as accurate as possible for a given country, but limited the analysis to countries where such reports are available.

This paper proposes two methodological approaches to compiling estimates in countries for which there is no secondary data. Sub-Saharan Africa is the region where the highest number of HRPs are available and so made a good testing ground.

Estimates based on secondary data analysis of the economic impact of internal displacement associated with conflicts in 13 sub-Saharan countries are reported in table 1. They served as the basis to project results to sub-Saharan African countries where no secondary data is available, using linear regression and K-nearest neighbour methods.

Adding estimates based on secondary data analysis and those based on modelled projections for all sub-Saharan countries affected by internal displacement associated with conflict produces a figure for the total economic impact on the region in 2018 of $4 billion. This represents 0.4 per cent of GDP, a significant burden for an already struggling economy.

METHODOLOGY

This paper aims to estimate the economic impact of a year of displacement per IDP, hereafter simply "cost per IDP", in the areas of health, livelihoods, education, security and housing, for countries not covered by an HRP.

The main hypothesis of the analysis is that a country's socioeconomic situation is linked to the impacts of internal displacement in several ways, including:

- The country's ability to assist and protect IDPs
- The country's resilience to and ability to recover after crises
- Opportunities for IDPs in host areas, including income-generating activities and education
- The ability of host communities to accommodate IDPs and face subsequent challenges

The World Bank's database contains around 1,500 indicators of socioeconomic development that could have been used as an input dataset for the analysis. Some, however, were not helpful to the analysis or were missing too many values.

TABLE 1: Economic impact estimates in input countries

ISO 3 code	Country name	Average number of IDPs/year, millions	Costs in USD in the following dimensions:						Cost per IDP in USD	Cost per IDP in purchasing power parity, international dollars
			Housing	Livelihood	Education	Food	Health	Protection		
CAF	Central African Republic	0.5	91	75	23	183	50	35	458	824
SSD	South Sudan	1.58	82.45	81	22	153	38	30	406	1912
SOM	Somalia	0.43	82.78	26	36	128	30	50	353	847
ETH	Ethiopia	0.59	65	120	3	120	12	6	326	749
NGA	Nigeria	1.6	70.6	54	9	99	16	35	284	667
CMR	Cameroon	0.18	50	168	13	100	13	20	297	772
SDN	Sudan	2.96	24.1	144	21	47	14	16	266	498
BDI	Burundi	0.07	73	45	4	56	14	22	213	540
TCD	Chad	0.11	80	53	19	156	80	65	453	1302
MLI	Mali	0.13	126	59	16	134	12	50	397	986
NER	Niger	0.12	84.125	73	28	255	25	70	535	1445
COD	Democratic Republic of the Congo	2.72	59.5	52	21	95	17	20	264	468
COG	Republic of the Congo	0.062	70.5	65	20	124	25	26	330	1078

Removing them left around 900, many of which were strongly correlated and did not yield any additional information. A principal component analysis showed that 40 components would be enough to describe the full variability of socioeconomic indicators in sub-Saharan Africa.

The analysis also drew on the dataset described in table 1. The 13 input countries are a relatively homogeneous sample both in terms of national income - all are low or lower-middle income countries - and because all are experiencing internal displacement associated with conflict or violence.

Using economic impact estimates based on secondary data analysis and the World Bank's socioeconomic indicators as input datasets, estimates of the cost per IDP in the 35 sub-Saharan countries not included in table 1 - the target countries - were compiled.

Projecting economic impact estimates from a limited sample to a large group of countries is complex, and one issue was the large size of the World Bank dataset. The methodology had to identify the most relevant indicators, to avoid overfitting input data and to preserve the interpretability of the results.

To this end, two different approaches were used:

- The first approach used linear regression to select one representative indicator as a proxy for the cost per IDP in each of the following areas: education; health, which encapsulates food and healthcare; housing; livelihoods and security. IDMC had previously identified these areas as those most affected by internal displacement. The indicators were selected from among those that showed a clear correlation with the cost per IDP in countries where secondary data was available. They were then used to predict the cost per IDP in the other countries by means of a linear model. This approach is simple and easy to interpret.

- In the second approach, all of the World Bank indicators that presented a significant correlation with the cost per IDP in the input countries were used. A K-nearest neighbour analysis was then used to compile estimates of the cost per IDP in the target countries on the basis of their socioeconomic similarity.

The two approaches can be considered complementary, so as a final step, their results were compared and combined to crosscheck their reliability and arrive at more robust estimates.

LINEAR REGRESSION METHOD

The first step in this approach was to remove all of the World Bank's socioeconomic development indicators that did not show a clear relationship - |R| > 0.4 - with the cost per IDP for the input countries.[2]

That reduced their number from 900 to 230, of which only about 80 were independent indicators. For each dimension used in the economic impact estimates, one well-correlated and particularly representative indicator was selected as proxy for the cost per IDP. A list of the selected indicators is provided in table 2.

TABLE 2: Indicators selected for each dimension and corresponding correlation coefficient with cost per IDP values

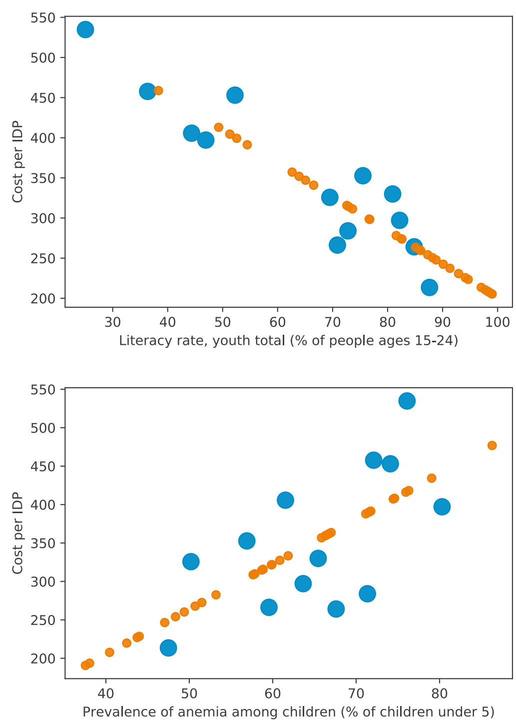
Dimension	Indicator	R
Education	Literacy rate, youth total (% of people ages 15-24)	-0.90
Health: Food	Prevalence of anaemia among children (% of children under 5)	+0.66
Health: Healthcare	Immunisation, DPT (% of children ages 12-23 months)	-0.57
Housing	Improved sanitation facilities (% of population with access)	-0.79
Livelihood	Crop production index (2004-2006 = 100)	+0.65
Security	Armed forces personnel (% of total labour force)	-0.52

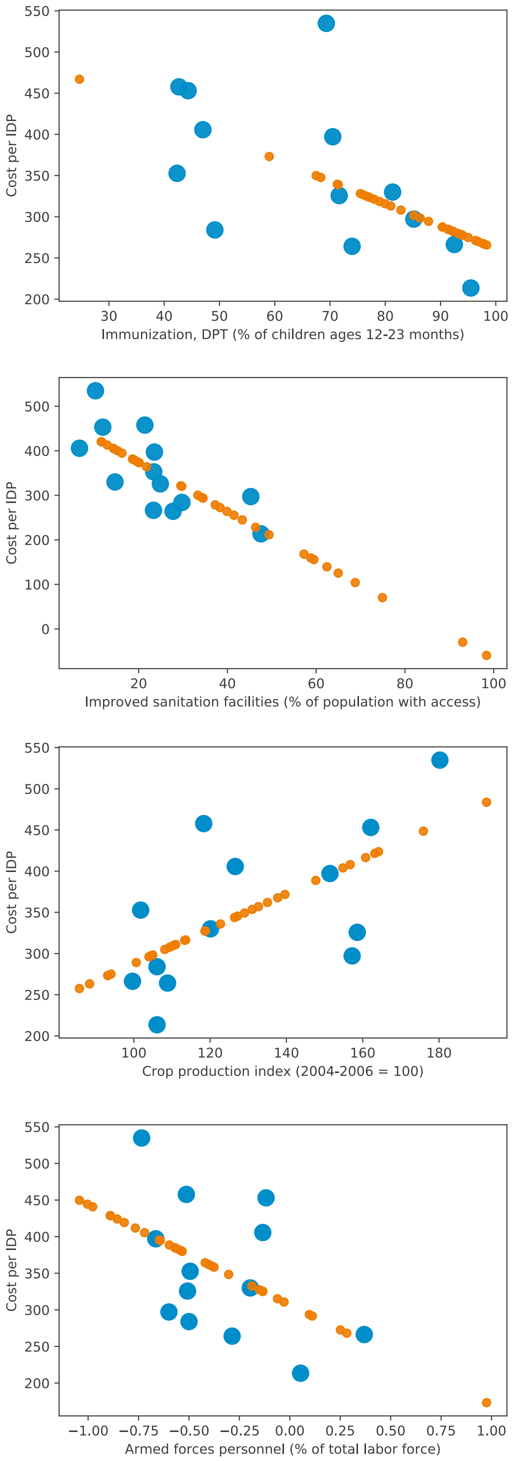
For each indicator, the best linear relation is found

$$Cost\ per\ IDP\ (c) = a_i * X_i(c) + b_i$$

where $X_i(c)$ is the value of the indicator i for the country c, and a_i and b_i are the parameters of the model. These linear relations were used to estimate the cost per IDP for each of the target countries (see figure 1). Six different predictions, one per dimension, were made for each country, and their median calculated to yield a single figure.[3] The level of associated uncertainty was given by the standard deviation of the six estimates. The results are provided in table 4.

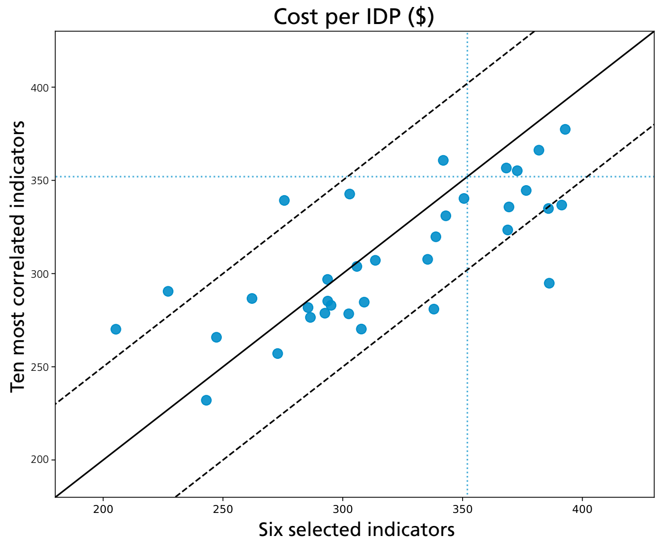
FIGURE 1: Cost per IDP vs the selected indicators for input countries (large blue dots) and from the corresponding linear regression model for target countries (small orange dots)





In principle, the linear regression model allows the economic impact of internal displacement to be projected for countries with quite different socioeconomic development from the input group. For the "percentage of population with access to improved sanitation facilities" indicator in figure 1, for example, countries in the input sample always have values below 50 while nine target countries have values between 50 and 100. In Equatorial Guinea, 75 per cent of the population has access to improved sanitation facilities, corresponding by linear regression to a cost per IDP of $70, which is very low compared with the figures for input countries.[4]

FIGURE 2: Comparison of the estimated cost per IDP from the six indicators shown in table 2 and from the 10 best correlated. Vertical and horizontal dotted lines correspond to the average value from input countries



The model has the potential to produce extreme predictions, and consequently significantly wrong forecasts when the linear regression assumption fails. This risk was reduced, however, by taking the median of the six different predictions for each country.

The differences in the predicted cost per IDP from each linear model was also a good check of the reliability of the predictions. The expectation was to find a large variation among the country predictions when the linear relation was not well verified or determined, making it impossible to provide reliable estimates. When the standard deviation was larger than 30 per cent of the median value, predictions were assumed to be unreliable. This was the case for eight countries: Angola, Cabo Verde, Equatorial Guinea, Mauritius, Rwanda, Seychelles, South Africa and The Gambia. For the six countries where the standard deviation was between 20 and 30 per cent of the median, the predictions are flagged as uncertain (see table 4).

One issue with this method is that predictions could be dependent on the arbitrary choice of the selected indicators. To verify that results were robust in terms of indicator selection, the analysis was repeated using the ten most correlated - corresponding to a correlation coefficient |R| >= 0.65 - and independent indicators.[5] As figure 2 shows, the results were compatible with previous predictions inside an uncertainty of about $50. It is interesting to note that in both cases most of the estimates are below the average value of $352 found in the input sample. This could mean that input countries are typically biased to high values of cost per IDP, but must be investigated further.

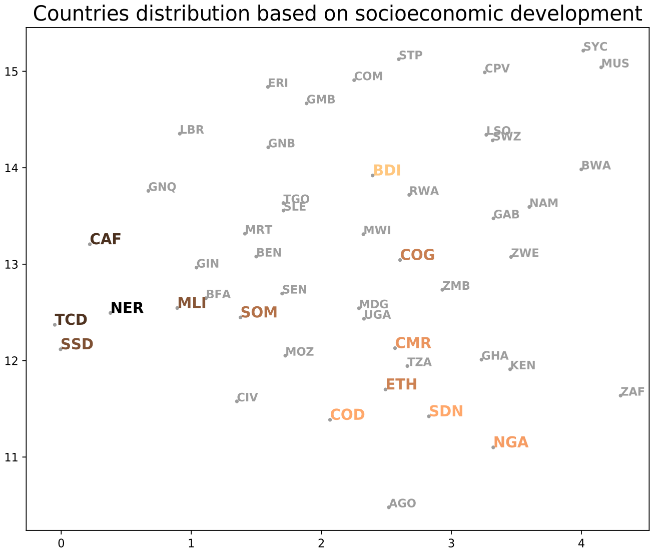
K-NEAREST NEIGHBOURS METHOD

The second approach exploited the information provided in the World Bank database as much as possible. All the 230 indicators that showed a correlation of |R| > 0.4 with the cost per IDP for input countries were used for the analysis.

The t-SNE algorithm, a technique to visualise high-dimensional data in a two-dimensional space, was used as a simple way of visually checking if there was a link between the socioeconomic indicators globally and the economic impacts of displacement.[6] Figure 3 shows the values of the 230 correlated World Bank indicators projected by the t-SNE algorithm onto a plane. Each point corresponds to a country. This is done in such a way that similar countries in terms of socioeconomic indicators are plotted by nearby points and dissimilar countries are plotted by distant points with high probability.

All sub-Saharan countries are shown, with the input countries highlighted in a colour that reflects their cost per IDP value: bright colours for lower costs, as for Burundi, Nigeria and South Sudan; dark colours for higher costs, as for the Central African Republic (CAR), Chad and Niger. The "dark" countries tend to sit in the left-centre area of the graph, while with the exception of Burundi the "bright" ones are concentrated in the bottom right-centre. This indicates a clear relation between position in the graph and cost per IDP. Tanzania and Uganda sit close to Cameroon and Ethiopia, meaning they would be expected to have a similar cost per IDP.

FIGURE 3: Distribution of countries, referred to by ISO 3 code, after t-SNE projection.



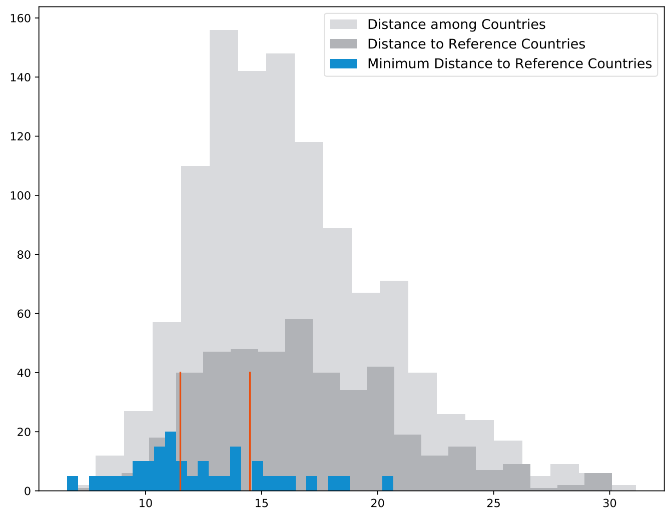
The cost per IDP for those shown in small grey letters is unknown. Input countries are shown in larger text, with colours reflecting the cost per IDP (see the text)

The K-nearest neighbour algorithm is a simple and suitable tool for regression in very high-dimensional problems such as this.[7] It makes an "educated guess" of a data point based on the input points that are most similar to it.

Figure 3 helps to understand how the K-nearest neighbour method works. For each country, the distance to all the other countries on the plane, and in particular to the input countries, is computed. The distance can be seen as a measure of similarity, with a relatively small distance indicating a similar level of socioeconomic development. Each country with an unknown cost per IDP is assigned the average value from its nearest neighbours with a known cost. In practice, this is not done in the projected plane but in the multi-dimensional space the indicators define.

K is a free parameter of the model. A large K value tends to smooth out results, averaging over a large number of countries, with estimates expected to be close to the mean of the sample. A small K value means estimates are based on only a few neighbours and could be biased as a result. For the purposes here, K = 3 and a distance-weighted average of the values was applied to give more relevance to the nearest country.

FIGURE 4: Histogram of the distance between all sub-Saharan countries (light grey); and between the 35 target countries and the 13 input countries (grey).



The blue histogram represents the distance between target countries and the closest input country, with the values multiplied by five to make them more visible

Figure 3 also illustrates some possible issues with the K-nearest neighbour method. Some countries sit far from any input countries, meaning there is no "similar" country with a known cost per IDP. The K-nearest neighbour estimates produced for these countries should be taken with caution or rejected. It is useful to look at the distribution of distance among countries, as shown by the blue histogram in figure 4.

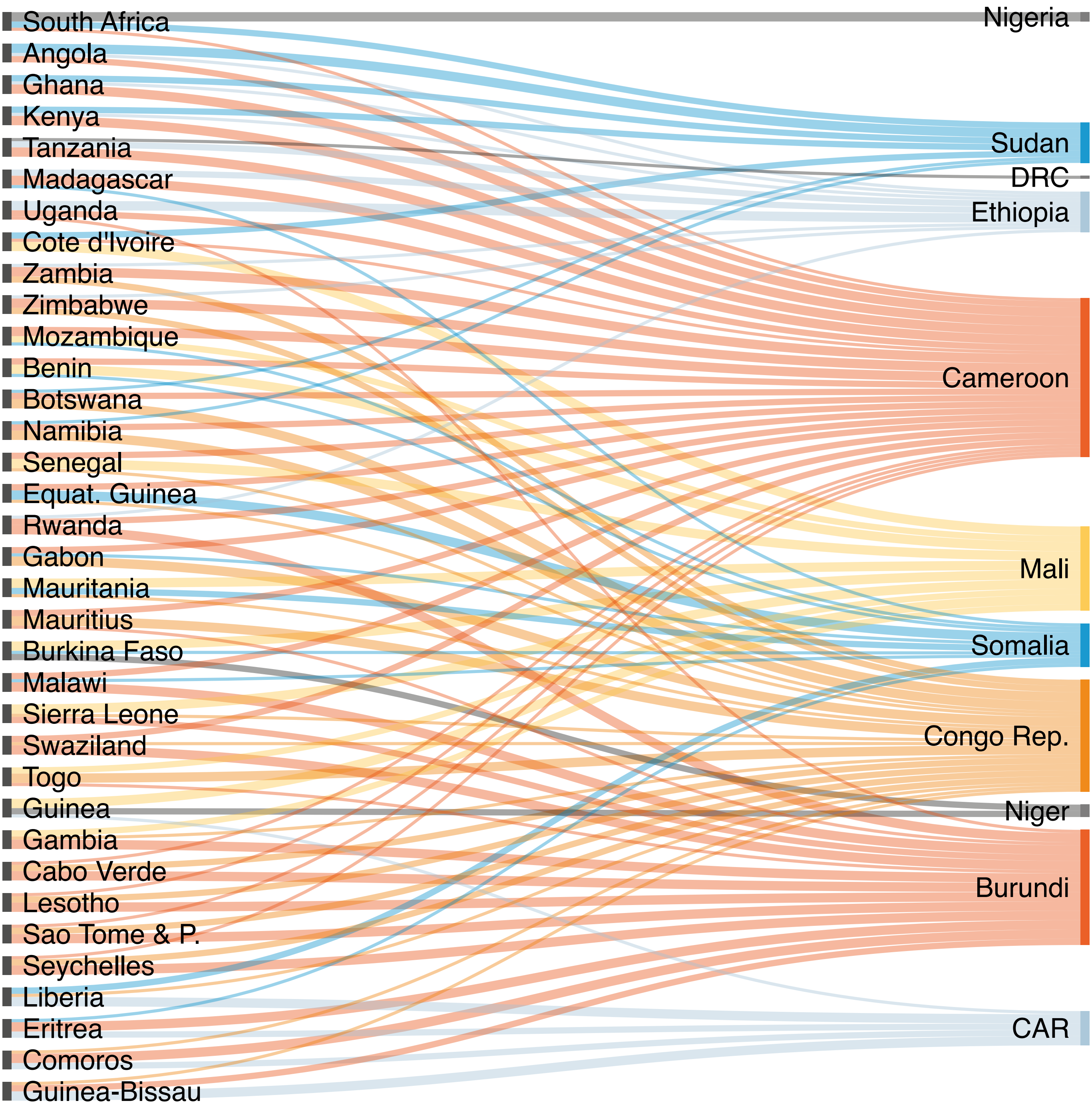
Two countries are considered close or similar in terms of socioeconomic development if their distance d falls on the left-hand side of the histogram, before the peak at $d{\sim}15$ (see the blue histogram). If a target country has no input country inside a range less than 14.5, K-nearest neighbour estimates should be considered unreliable (see the blue histogram). This was the case for nine countries: Angola, Botswana, Cabo Verde, Eritrea, Liberia, Mauritius, São Tomé and Principe, Seychelles and South Africa. Six of them are among the countries the linear regression method also flagged as unreliable. The estimates for target countries for which the closest input country is in the range of $11.5 < d < 14.5$ are flagged as uncertain.

The closest three input countries to all of the target countries are reported, with the respective distances, in table 3 and figure 5. Four input countries are often found closest to target countries, making them the most relevant ones for K-nearest neighbour predictions: Burundi comes up 10 times, Cameroon and Mali seven and Congo five. Chad and South Sudan never appear in the table and so were not used in K-nearest neighbour predictions.

TABLE 3: Target countries with their three closest input countries and the corresponding distance

ISO code	Country	First K-nearest neighbour	Distance to 1st K-nearest neighbour	Second K-nearest neighbour	Distance to 2nd K-nearest neighbour	Third K-nearest neighbour	Distance to 3rd K-nearest neighbour
AGO	Angola	SDN	17.2	CMR	17.2	ETH	17.9
BEN	Benin	MLI	9.6	CMR	10.8	SOM	11.3
BFA	Burkina Faso	MLI	6.6	NER	9.3	SOM	11.7
BWA	Botswana	COG	15.8	CMR	16.9	SDN	17.4
CIV	Côte d'Ivoire	MLI	12.2	SDN	12.8	CMR	12.9
COM	Comoros	BDI	12.9	CAF	16.1	COG	16.3
CPV	Cabo Verde	BDI	16.3	COG	16.6	CMR	17.6
ERI	Eritrea	BDI	14.9	CAF	15.3	SOM	15.5
GAB	Gabon	COG	10.3	CMR	12.5	SOM	15
GHA	Ghana	CMR	9.5	SDN	10.8	ETH	12.4
GIN	Guinea	MLI	8	NER	10.4	CAF	10.8
GMB	Gambia	BDI	14.1	MLI	14.8	COG	15.4
GNB	Guinea-Bissau	CAF	10.8	BDI	11.9	COG	13.3
GNQ	Equatorial Guinea	SOM	13.6	CMR	13.6	COG	14.3
KEN	Kenya	CMR	11.1	SDN	11.5	ETH	12.1
LBR	Liberia	CAF	14.7	SOM	15.1	COG	15.2
LSO	Lesotho	BDI	14	COG	15.4	CMR	15.8
MDG	Madagascar	CMR	11.2	ETH	13	SOM	13.6
MOZ	Mozambique	CMR	11.3	MLI	11.7	SOM	11.8
MRT	Mauritania	MLI	10.8	SOM	11.3	COG	11.9
MUS	Mauritius	COG	18.8	CMR	18.9	BDI	19.6
MWI	Malawi	BDI	11	CMR	11.5	SOM	13.1
NAM	Namibia	COG	12.6	CMR	13.1	SDN	13.3
RWA	Rwanda	BDI	9.2	CMR	12.7	ETH	12.9
SEN	Senegal	MLI	9.9	CMR	10.8	COG	11.7
SLE	Sierra Leone	MLI	11.4	BDI	11.4	COG	11.7
STP	São Tomé and Principe	BDI	15.3	COG	15.9	CMR	17
SWZ	Swaziland	BDI	13.8	CMR	14.9	COG	15.1
SYC	Seychelles	BDI	20.7	COG	20.7	CMR	22.6
TGO	Togo	COG	11	MLI	11.6	BDI	11.7
TZA	Tanzania	CMR	8	ETH	11.3	COD	12.4
UGA	Uganda	ETH	9	CMR	9.9	BDI	11
ZAF	South Africa	NGA	17.9	SDN	19.3	CMR	20.2
ZMB	Zambia	CMR	10.7	COG	10.7	ETH	11
ZWE	Zimbabwe	CMR	12.6	COG	13	ETH	13.4

FIGURE 5: Each target country connected to its closest three input countries. The thickest connecting lines show the closest countries, and the thinnest the third-closest

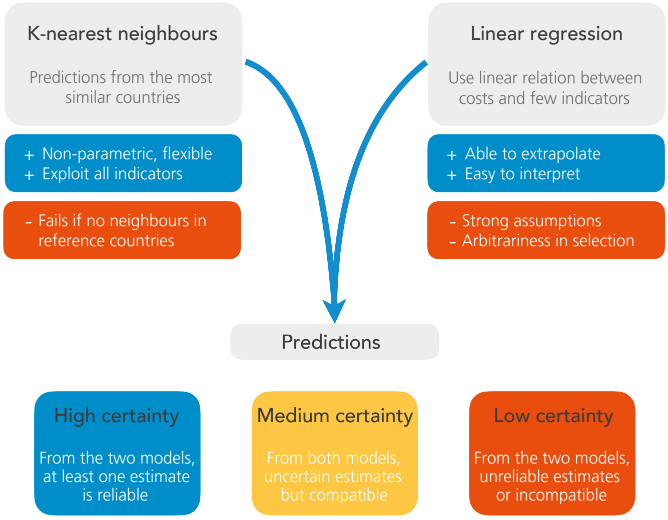


K-nearest neighbour predictions are reported in table 4, and in figure 7 in comparison with linear regression results. Because the K-nearest neighbour method averages over the existing data and avoids any kind of extrapolation, it can be considered a conservative approach. Predictions cannot be larger or smaller than the largest or smallest value in the input sample. The method also has the advantage of not requiring strong assumptions and depends only on few free parameters. The main disadvantage is that it yields poor or unreliable estimates for half of the countries.

COMBINING RESULTS: FINAL PREDICTIONS

Figure 6 summarises the methodologies used to estimate the cost per IDP in sub-Saharan African countries where no data was available, and shows their strong and weak points. Final predictions are then provided by joining previous results, taking their reliability into account on a case-by-case basis.

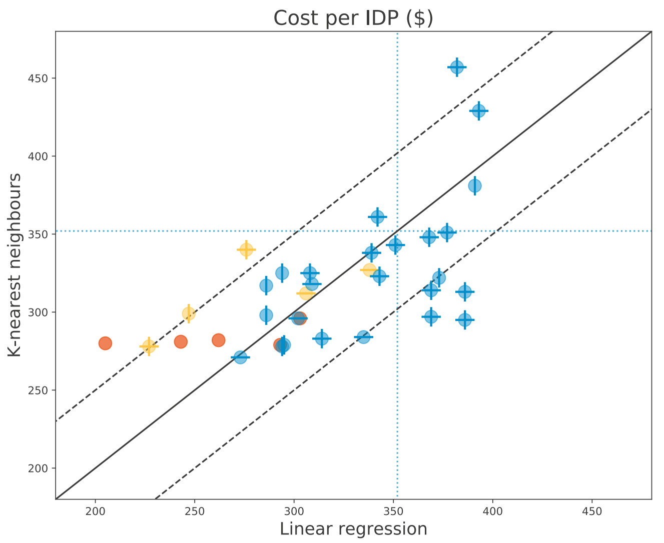
FIGURE 6: Sketch of the methodology employed to estimate the cost per IDP in target countries



Comparing estimates from the two models was an important way to crosscheck the reliability of their predictions. As figure 7 shows, there is generally good agreement between the results, which tend not to deviate by more than $50. The K-nearest neighbour method tends to provide estimates on a smaller range of values compared with the linear regression method, between $270 and $350, and only four countries have a cost per IDP larger than the input sample mean.

This is because of the way the predictions were computed. The K-nearest neighbour method averages over input countries. The three input countries that appear most often as neighbours to target countries are Cameroon, Burundi and the Republic of Congo, whose costs per IDP are $297, $213 and $330 respectively. The linear regression method provides estimates spread from $230 to $400, with ten countries over the input average.

FIGURE 7: Comparison of predictions from the two methods



Crosses show those obtained by averaging the two values, vertical bars those from the linear regression method and horizontal bars those from the K-nearest neighbour method. Colours indicate the reliability of the predictions.

These results can now be combined to obtain a single prediction for the cost per IDP in target countries. Reliability flags are used to define the level of certainty in the final predictions as follows:

High:
- Predictions from both methods are flagged as good and they are in agreement, meaning with a maximum deviation of 30 per cent. Their results are averaged.
- Only one prediction is flagged as good and is used as final prediction.

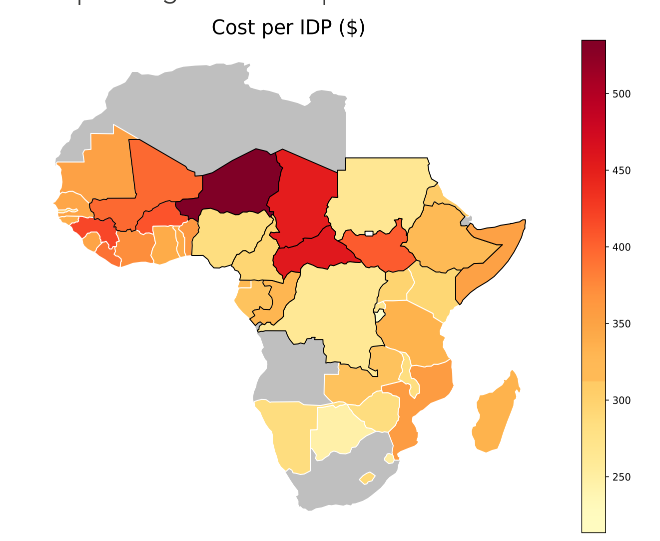
Medium:
- Both methods give predictions with medium certainty but they are in agreement, meaning with a maximum deviation of 30 per cent. Their results are averaged.
- One prediction has medium certainty and the other is low. The value of the former is used.

Low:
- Both methods fail to provide reliable predictions.
- The two methods provide estimates that deviate by more than 30 per cent.

The final estimates for the cost per IDP are reported in table 4. There are no trustworthy results for five countries: Angola, Cabo Verde, Mauritius, Seychelles and South Africa. These countries have distinct characteristics. Cabo Verde, Mauritius and Seychelles, for example, are small island developing states with a socioeconomic situation that differs broadly from that of the input countries. Predictions are not fully reliable for five other countries: Botswana, Eritrea, Equatorial Guinea, Swaziland and The Gambia.

Figure 8 is a "heat map" of the cost per IDP in sub-Saharan Africa. There are relatively homogeneous colours in certain geographic regions: high economic impacts of more than $350 in the north and north-west; average impacts between $300 and $350 in central Africa and low impacts of less than $300 in the south. This is likely to be the result of regional patterns of socioeconomic development that affect the cost per IDP.

FIGURE 8: Map of sub-Saharan countries with colours corresponding to the cost per IDP.



Countries with a black border are from the input sample, and those with a white border from the target group. Countries flagged with bad reliability are left in grey

TABLE 4: Predictions of cost per IDP in target countries

Country (high certainty)	Linear regression	Standard deviation	K-nearest neighbour	Minimum distance	Prediction
Benin	377	27	351	10	364
Burkina Faso	393	64	429	7	411
Côte d'Ivoire	373	39	322	12	373
Comoros	294	23	325	13	294
Gabon	308	36	325	10	317
Ghana	386	75	295	10	341
Guinea	382	40	457	8	420
Guinea-Bissau	339	38	338	11	339
Kenya	302	61	296	11	296
Liberia	391	45	381	15	391
Lesotho	294	52	278	14	294
Madagascar	343	55	323	11	333
Mozambique	368	51	348	11	358
Mauritania	342	62	361	11	352
Malawi	335	76	284	11	284
Namibia	286	32	298	13	286
Rwanda	273	90	271	9	271
Senegal	351	70	343	10	347
Sierra Leone	386	49	313	11	350
São Tomé and Principe	295	41	279	15	295
Togo	369	56	314	11	342
Tanzania	369	69	297	8	333
Uganda	314	54	283	9	299
Zambia	309	81	318	11	318
Zimbabwe	286	31	317	13	286
Country (medium certainty)					
Botswana	247	61	299	16	247
Eritrea	276	77	340	15	276
Gambia	306	94	312	14	312
Equatorial Guinea	338	142	327	14	327
Swaziland	227	55	278	14	253
Country (low certainty)					
Angola	303	91	296	17	300
Cabo Verde	293	91	279	16	286
Mauritius	243	95	281	19	262
Seychelles	205	82	280	21	243
South Africa	262	95	282	18	272

TABLE 5: Total economic impact of displacement associated with conflict in sub-Saharan target and input countries in 2018[9]

Target Country	Costs per IDP [$]	Average number of IDPs in 2018	Total Costs 2018 [M$]
Benin	364	1,750	0.64
Burkina Faso	411	23,450	9.6
Côte d'Ivoire	373	3,100	1.2
Ghana	341	2,500	0.85
Kenya	296	170,00	5
Madagascar	333	500	0.17
Mozambique	358	1,960	0.7
Sierra Leone	350	1,500	0.53
Uganda	299	5,150	1.5
Input Country			
Burundi	213	45,580	9.7
Cameroon	297	239,000	71
Central African Republic	458	665,000	305
Chad	453	128,750	58
Republic of the Congo	330	107,500	35.5
Democratic Republic of the Congo	264	3,780,500	998
Ethiopia	326	1,333,000	435
Mali	397	79,000	31.4
Niger	535	150,000	80
Nigeria	284	1,916,000	544
Somalia	353	321,000	113
South Sudan	406	1,884,000	765
Sudan	266	2,072,000	551
Regional			
Regional	350	12,931,240	4,017

These methods allow the economic impact of internal displacement associated with conflicts to be predicted for sub-Saharan countries on which there is no secondary data. Table 5 shows the predictions for conflicts that led to internal displacement in 2018. There are nine countries in which between 500 and 23,450 people were displaced throughout the year.[8] The economic impact is almost $10 million in Burkina Faso, $5 million in Kenya and about $1 million or less in the other countries.

Adding the estimates for the input and target countries produces a total figure for the economic impact of internal displacement associated with conflict in sub-Saharan Africa in 2018 of $4 billion.

CONCLUSION

The analysis presented in this paper focuses only on internal displacement associated with conflict. The same methods could in principle also be applied to that associated with disasters. Estimates of the economic impact of internal displacement based on secondary data analysis do not usually differ between the two causes.[10]

This analysis does not take into account the severity of crises, which also affects economic impacts. Costs and losses per IDP vary depending on whether crises are regional or national, short-lived or protracted, and whether they involve a small or large portion of the population. The effects of these factors will be examined in future work.

The methods proposed in this paper and the results they yield help to bridge a major knowledge gap on the consequences of internal displacement for economies. Revealing the significant financial cost of internal displacement on affected people and countries and on the international community should raise awareness on the importance of investing in prevention and rapid recovery.

NOTES

1. Estimates for another 13 countries worldwide will be soon published; IDMC, Multidimensional impacts of internal displacement, October 2018
2. Here R is Pearson's correlation coefficient that measures the linear correlation between two variables. Values close to 1 (-1) indicate a strong positive (negative) correlation, while R values close to 0 show no linear correlation.
3. In this case, the median is preferred to the mean, because it is less sensitive to outliers.
4. For this indicator, the cost per IDP becomes negative when the indicator values are larger than 80. This occurs for Mauritius and Seychelles. Negative values will be replaced with the lowest positive value found in the target countries, which is $70 in Equatorial Guinea).
5. Here is the list of indicators: Women who were first married by age 18 (% of women ages 20-24); Literacy rate, adult male (% of males ages 15 and above); Improved sanitation facilities, rural (% of rural population with access); Literacy rate, youth (ages 15-24), gender parity index (GPI); Lower secondary completion rate, total (% of relevant age group); School enrollment, tertiary, female (% gross); Population density (people per sq. km of land area); Primary education, pupils (% female); Arable land (hectares per person); School enrollment, primary, female (% gross).
6. See t-SNE web page by LJP van der Maaten
7. See, for example, "An introduction to kernel and nearest-neighbor nonparametric regression", Altman, N. S. (1992).
8. The average number of people displaced over the year is obtained by averaging the IDP stock figure from IDMC database at the end of 2017 and at the end of 2018.
9. Estimates for Somalia are based on the stock figure until August 2018, and those for Cameroon refer to the crisis in the country's Far North region.
10. IDMC, Unveiling the cost of internal displacement, February 2019

Cover photo: Simon, 11, from the Nuer tribe is staying in the POC3 camp in Juba with his father, four sisters and two brothers. He is invested in his studies and hopes to be a doctor someday, to help his father and the whole of South Sudan. Photo: NRC/Ingrid Prestetun, May 2018

Author
Marco Tucci
Data Analyst

IDMC contact
Christelle Cazabat
Researcher
christelle.cazabat@idmc.ch

IDMC
NRC, 3 rue de Varembé
1202 Geneva, Switzerland
www.internal-displacement.org
+41 22 552 3600
info@idmc.ch