Landscope rating system

Methodology for Tenure Risk Similarity Ratings

TMP Systems

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Landscope version 4.2

This document describes Landscope's methodology for producing Tenure Risk Similarity Ratings, based on 14 environmental, social and governance indicators in a given area, which were selected on the basis of their statistical association with tenure disputes.

This document provides information on how the underlying indicator values are rated and combined to produce the various Similarity Ratings. Details of the statistical analysis supporting this methodology can be found in the Statistical Evidence of Tenure Risk document, available here.

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1. Executive Summary

Landscope is a system for measuring the tenure risk, a term TMP Systems created to describe the financial risk associated with local opposition to a real asset. Its main output is an 'Overall Similarity Rating' of the area surrounding a point selected by the user, which describes how similar that queried location is to places where tenure disputes have occurred.

This process provides 4 national-level indicators and 10 sub-national-level indicators, weighted according to their statistical association with tenure disputes. Each of these indicators is rated on a scale of 0-100, with 0 representing indicator levels rarely or never associated with tenure disputes, and 100 representing indicator levels associated with tenure disputes, but rarely or never found in places where tenure disputes have *not* occurred.

These ratings are assessed relative to the average scores for the region (Africa, Latin America or Asia) for each indicator to produce a Relative Similarity Rating for each indicator, and grouped into three 'Context Factors': Local Conditions, National Conditions and Local Behavior.

These 'Overall Similarity' classifications are:

- **Dissimilar**, which is when we see that the data in the queried location looks very different from places where tenure risk has been a problem.
- **Inconclusive.** This either means that the data patterns aren't clear, or we don't have enough data to have full confidence in the results.
- **Partially similar**, when there are only one or two particular aspects of the location which are similar to places with tenure risk issues
- **Similar.** This is when there is a broad similarity between tenure risk hotspots and the place you chose, but not to the degree where it's alarming.
- **Highly similar**, which means exactly what it sounds like: the queried location looks very much like places where tenure risk has been a problem.

The system presents further information to help the user understand the local context and manage identified issues. The additional outputs are: (i) Similarity Ratings for local and national conditions and local behavior, (ii) guidance for users on how to deal with the specific issues identified in the area, (iii) alerts about particularly problematic issues, (iv) a map showing additional relevant information, and (v) charts displaying indicator ratings in comparison with regional averages.

Landscope is not designed to replace expert insight, nor eliminate the need invest time and money to understand the human factors that impact assets' performance. Its purpose is to help users to structure that process, rationalize its cost against potential losses and make due diligence more efficient and effective.

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2. Introduction

Landscope is a system for measuring tenure risk, a term we created to describe the financial risk associated with local opposition to a real asset. This kind of opposition to investments is very common across Africa, Asia and Latin America, often causing significant financial losses and operational headaches. Over the last seven years, we have compiled a database of more than 600 tenure disputes, each studied in detail to inform the development of Landscope system.

The system applies a new approach to analyzing geospatial data about political, social and environmental issues. It is designed to help companies and investors in emerging markets to prepare a proper assessment of tenure risk at project, supply chain or portfolio level. Landscope will not replace expert insight, nor eliminate the need to invest time and money to understand the human factors that impact asset performance. But it will help users to structure that process, rationalize its cost against potential losses and make due diligence more efficient and effective.

Landscope provides a geographically specific assessment of the risk of dispute, based on sub-national data wherever possible. Its overall method is analogous to approaches developed by criminologists for forecasting risks of crime based on contextual factors, in particular to Risk Terrain Modelling, which provides a methodology to “articulate vulnerable places at the micro-level.”[1]

Our analysis of the ESG factors relevant to tenure risk allows us to rate them on a unified scale which provides both an intuitive sense of the overall level of similarity to places where tenure disputes have occurred, and the extent to which different factors contribute to that overall similarity. Landscope’s rating methodology grounds these scores on empirical evidence of the relationship between contextual factors and tenure disputes, drawing on the best available data on the incidence of real-world cases of dispute.

This differentiates Landscope from other ESG ratings, which are usually based on analysis conducted at the company or country level, or which depend ultimately on qualitative assessments. Landscope provides an unprecedented level of geographic specificity for operational risk in emerging markets. It is also unique, to the best of our knowledge, in applying a quantitative assessment of tenure risk at any level of specificity.

The methodology has been built with three additional features that are important to note: replicability, adaptability, and the ability to improve over time. The statistical analysis we conducted is replicable to other problems relating to private investment in emerging markets, such as labor rights, or any operational risks relating to the ESG context of an asset.

The rating methodology is adaptable to the incorporation of any ESG data, and to any project where ESG conditions can determine success. In Landscope, we have applied it to

1 Kennedy, L.W. and Dugato, M., “Forecasting Crime and Understanding its Causes. Applying Risk Terrain Modeling Worldwide”, 2018, European Journal on Criminal Policy and Research, https://doi.org/10.1007/s10610-018-9404-3

quantify tenure risk, but it is equally applicable to identifying opportunities – for example, target locations for poverty alleviation, or gaps in key infrastructure or service provision.

Finally, the weights and combinations of discrete indicators and context factors can be improved as better information emerges. As new data on the incidence of tenure disputes or their relationships with ESG factors appear, the model's predictive power will increase.

In the first section of this document, we describe how we selected the 14 indicators of the social, political and environmental context, which Landscope uses to produce a rating for the location being queried. The indicators were chosen following a systematic statistical analysis, (they are described fully in Appendix 1).

The second section explains the methodology behind the normalized 0-100 rating scales and weighting applied to each indicator. It explains how the system adjusts indicator ratings based on the region the queried location is in, and combines them to produce a single rating for an area – the Relative Similarity Rating – and into three groups of indicators – the Context Factor Ratings (Local Behavior, Local Conditions, and National Conditions).

In the last section, we describe how Landscope uses the Context Factor Ratings and the Relative Similarity Ratings to produce a classification of the Overall Similarity of the area to places where tenure dispute has occurred. This classification is either 'highly similar', 'similar', 'partially similar', 'dissimilar', or 'inconclusive' (with 'inconclusive' including places with insufficient data for Landscope to make a reliable assessment).

3. Indicator selection

Our statistical assessment of more than 50 indicators of ESG context identified seven indicators of national-level conditions, and 16 at the sub-national level, each showing a direct correlation with known incidents of tenure dispute.[2]

We conducted analyses of the association between tenure disputes and ESG indicators at two levels, the first based on national-level indicators and the second based on indicators that provide sub-national granularity. This section summarizes the results as they relate to Landscope's scoring.[3]

National indicators

There are two areas where national-level indicators are of particular interest: governance and poverty. Governance represents a blind spot for geospatial analysis: the only globally comparable, high quality, quantitative assessments of governance are all resolved at the national level, although we know from our own and others' research that governance is a major factor in many tenure disputes.[4]

We compared the number of tenure disputes in each country covered by the governance and poverty datasets with the level of each indicator, allowing us to observe correlation between the two. The number of cases per US dollar of foreign direct investment ($FDI) were counted for each country, as the number of disputes that occur *in relation to investment levels* offers a good reflection of the incidence of tenure dispute, in proportion to national economic activity.

The relationship between each indicator and the number of cases per $FDI was investigated through linear regression models, with indicators or the number of cases per $FDI occasionally log-transformed to create better models. The strength of the linear relationship between the number of cases per $FDI and the national indicators was quantified by calculating Pearson's coefficients.

Our analysis revealed three national ESG datasets with strong associations to tenure risk:

1) The World Bank's Worldwide Governance Indicators dataset[5]
2) The UNDP's Human Development Index[6]
3) Transparency International's Corruption Perceptions Index[7]

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2 Summarised in the Statistical Evidence of Tenure Risk document, available at [link].

3 More details on these analyses are provided in the companion report to this one, available at [link]

4 See, for example, de Schutter (2015) Tainted Lands: corruption in large-scale land deals, International Corporate Accountability Roundtable and Global Witness, and Kircherr et al (2016) Multi-causal pathways of public opposition to dam projects in Asia, Global Environmental Change 41, 33–45.

5 http://info.worldbank.org/governance/wgi/#home

6 http://hdr.undp.org/en/content/human-development-index-hdi

7 https://www.transparency.org/news/feature/corruption_perceptions_index_2017

While we found statistically significant associations with a large number of indicators from these datasets, we do not use all of them in our tenure risk model. This is because many of them – particularly the governance indicators – are highly collinear: there is a large amount of correlation among the indicator themselves, independent of their tenure risk associations. Including them all in a rating model would not increase the power or efficacy of the model, and may in fact skew results.

In simple terms, we found that where one indicator value is high, other indicators in the same datasets are also likely to be have high values. For example, places with poor human development also typically have lower regulatory quality and government effectiveness.

We conducted extensive testing to reveal the exact extent of this collinearity, and used the results to inform our development of the overall risk score model. We created a multiple regression model, and calculated the variance inflation factor (VIF) of each indicator, to identify which national indicators should be used in the model. VIF gives an indication of how the multicollinearity of an indicator (its collinearity with multiple other indicators) is affecting the regression model. In other words, it provides a quantification of how much each indicator correlates with the other indicators, in terms of the efficacy of the model.

We started with a model that included all the indicators where we had found an association with tenure risk. Our model's initial construction applied the greatest weight to the indicators that had the strongest associations with the incidence of tenure dispute

We then removed indicators from the model that had a high VIF and recalculated the model. If two indicators both had an equally strong association with tenure risk, but one was also strongly correlated with a third indicator available to the model, we would select the indicator without the additional correlation. This process was repeated until we had a regression model in which each indicator had a suitably low VIF.

Sub-national indicators

The sub-national datasets where we found a statistically significant association with tenure risk cover a range of environmental and social factors. For these assessments we compared average or total values[8] for the area surrounding tenure dispute locations with the areas surrounding project locations where no dispute was reported, from the same sector.

We identified which would be most powerful for predicting tenure risk by comparing the indicator values in the tenure dispute group with the values for the control group, using standard statistical techniques.[9] This produced a list of indicators that had a statistically significant relationship with tenure risk.

8 Averages were used for data where scores (typically continuous) or ratings are applied to each location in an area, such as poverty rates or the rate of change in population levels, whereas in cases where data consisted of large numbers of 'real' objects (such as numbers of people or conflict events), counts were used.

9 Mann-Whitney-U, Student's T-test etc., as described in the Statistical Analysis paper: https://landscope.info/landscope_statistical_evidence.pdf

We consistently found statistically significant associations with the incidence of tenure disputes in five of the tested datasets:

- Oxford Poverty and Human Development Initiative's Multidimensional Poverty Index[10]
- The Gridded Population of the World dataset (v4)[11]
- ETH Zurich university's georeferenced Ethnic Power Relations Power dataset[12]
- The World Database on Protected Areas[13]
- GlobCover[14]

Again, there were a number of indicators which showed an association with tenure risk, and we sought to reduce the number through a similar testing of collinear data points. Unlike our treatment of the national-level data, logistic regression modelling using the sub-national indicators did not provide insightful results.[15]

Instead, we selected the sub-national indicators for the overall tenure risk model based on the strength of their association with the incidence of tenure disputes, alongside an evaluation of which indicators provided the greatest breadth of risk factors. In practice, this meant that we excluded a number of the MPI indicators for which the associations were not as strong as for others, while still retaining coverage of different, relevant dimensions of poverty.

Indicators used in the Similarity Rating Model

The indicators that are used in the Similarity Rating Model are drawn from a broad spectrum of social, economic, political and environmental factors. We could have taken the usual ESG approach here, and put all the indicators into environmental, social or governance buckets, but in our view this taxonomy is not well-suited to the reality of tenure risk.

Rather, we have thought about the problem from the perspective of local populations, and tried to determine which indicators describe conditions that the local population cannot really change, and which describe behavior, which are decisions that the local populations take in reaction to those conditions. Because there are so many things that are out of the control of local people, and decisions that are taken in faraway capitals, we divide the indicators of

10 https://ophi.org.uk/multidimensional-poverty-index/

11 http://sedac.ciesin.columbia.edu/data/collection/gpw-v4

12 https://icr.ethz.ch/data/epr/geoepr/

13 https://www.protectedplanet.net/c/world-database-on-protected-areas

14 http://due.esrin.esa.int/page_globcover.php

15 This was because the results were based on a comparison of a control group with the tenure dispute group, and differences in sample sizes of the two groups skewed the results, resulting in selections of indicators which did not accurately reflect relationships with tenure risk.

conditions in two categories – national and local – and add a third category describing local behavior.

Table 1 shows the specific indicators in each group that are used in Landscope's overall similarity rating model. [16]

Factor	**Indicator (Dataset)**
National Conditions	Corruption (Corruption Perceptions Index)
	Government Effectiveness (Worldwide Governance Indicators)
	Human Development Index (Human Development Index)
	Political Stability (Worldwide Governance Indicators)
	Voice and Accountability (Worldwide Governance Indicators)
Local Conditions	Access to Electricity (Multidimensional Poverty Index)
	Access to Power (Georeferenced Ethnic Power Relations)
	Protected Areas (World Database on Protected Areas)
	Relative MPI - local / national level (Multidimensional Poverty Index)
	Vulnerability to Poverty (Multidimensional Poverty Index)
Local Behavior	Asset ownership (Multidimensional Poverty Index)
	Child School Attendance (Multidimensional Poverty Index)
	Land Use Change (GlobCover)
	Population Change (Gridded Population of the World v4)

Table 1: the indicators Landscope uses to derive its ratings[17]

It is worth reiterating that we discovered other indicators with a statistically significant relationship with tenure risk. In many cases these relationships were strong, but their collinearity with other indicators meant that, in combination, it actually made the model less effective to include them all.

Section 4 describes the rating methods by which Landscope processes the 14 indicators into an Overall Similarity Rating and other outputs.

16 Appendix 1 gives a full description of the datasets used by the Landscope Similarity Rating model, the provider of the dataset, and the indicators used from that dataset.

17 See Appendix 1 for full descriptions of the indicators

4. Similarity rating process

Landscope provides one of five possible classifications of Tenure Risk Similarity for the area selected by the user, based on the similarity between the indicator profile of the queried location, and that of places where tenure disputes have occurred in the past. These 'Overall Similarity' classifications are:

- **Dissimilar,** which is when we see that the data in the queried location looks very different from places where tenure risk has been a problem.
- **Partially similar,** when there are one or two particular aspects of the location which are similar to places with tenure risk issues.
- **Similar,** when there is a broad similarity between tenure risk hotspots and the queried location, but not to an alarming degree.
- **Highly similar,** which means the queried location looks very much like places where tenure risk has been a problem.
- **Inconclusive,** meaning that the data patterns are not clear, or we do not have enough data to have full confidence in the results.[18]

Landscope produces these classifications by processing indicator data in five steps:

- Indicator Scoring: calculates discrete scores of 0-100 for each of the 14 indicators in the queried location.
- Relative Regional Weighting: weights the indicator scores for the queried location according to the average indicator scores for the country it sits in, relative to the regional average indicator scores.
- Relative Similarity Rating: combines the 14 weighted indicator scores, to provide a single rating that reflects the range of key factors that influence tenure disputes.
- Context Factor Rating: groups indicators into three baskets – Local Conditions, National Conditions, and Local Behavior.
- Overall Similarity Rating: combines Context Factor Rating and Relative Similarity Rating for the queried location to produce a final classification.

Indicator scoring

We have developed a replicable, standardized method for scoring underlying indicator values. It can be applied to any range of continuous data, and result in a standardized scoring of 0-100, where 0 represents the lowest possible association with tenure risk, and 100 the highest. This will make it relatively straightforward to introduce new indicators into the similarity rating methodology, as better data becomes available.

18 In some instances, where the underlying datasets do not cover the area selected by the user and Landscope lacks sufficient indicator data to make a reliable assessment, the website will return an 'Insufficient Data' summary.

To calculate how a given indicator value should be rated on the 0-100 scale, we look at the distribution of values in places where tenure dispute has not occurred, and compare it with the distribution of values in places where tenure disputes have occurred.[19]

Figure 1, below, illustrates the rating process. To understand the distribution of indicator values we divide the total range of indicator values into quartiles (i.e. with a quarter of the total number of values in each). In Figure 1, the boxes in the middle represent the middle two quartiles, and the 'whiskers' represent the highest and lowest quartiles (with outlier values marked as dots).

In this example, a quarter of the places where tenure dispute had not occurred (the 'Control locations' on the left) had an indicator value of greater than 3.3. But for places where tenure disputes *had* occurred ('Conflict'), half of all locations had indicator values greater than 3.3. This tells us that indicator values higher than 3.3 should receive a correspondingly higher rating on the 0-100 scale, as they are much more common in non-dispute locations than in dispute locations.

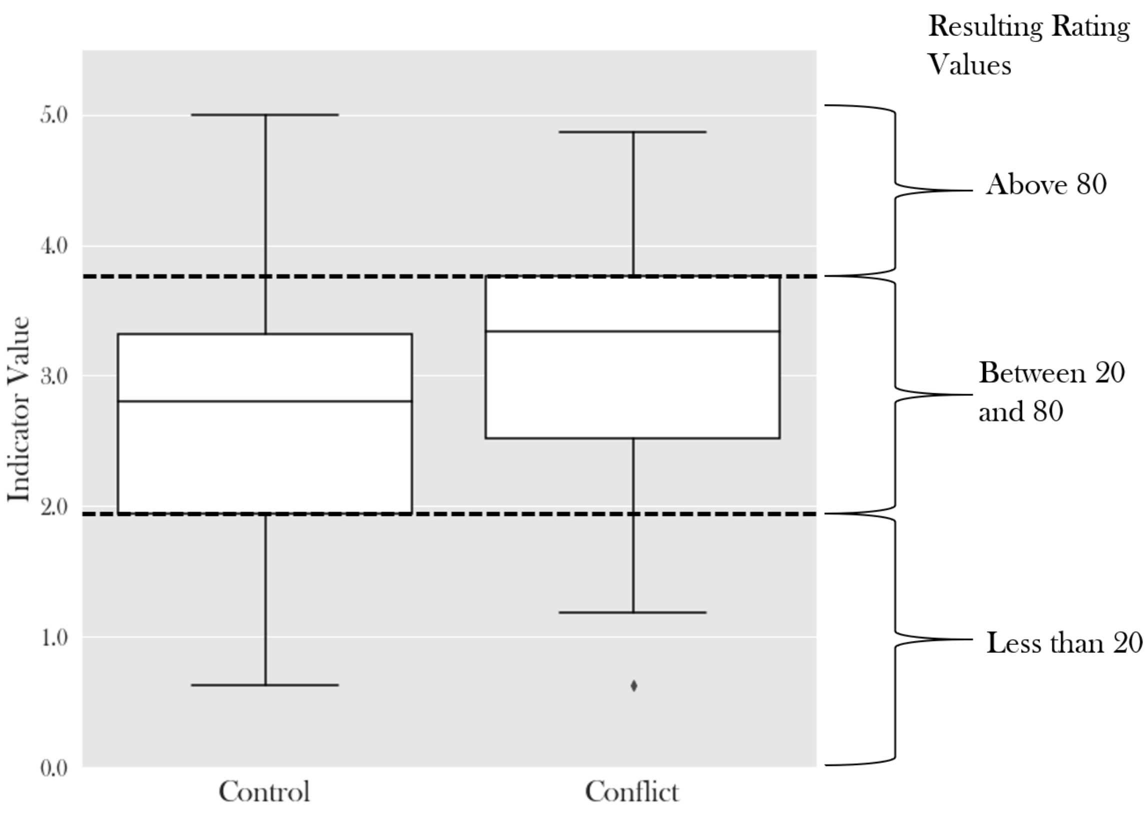

Figure 1: Illustrative example of the application of Landscope scores to underlying indicator values by comparing project locations where tenure disputes occurred to project locations where they did not

Figure 1 illustrates exactly how the ratings values (to the right of the chart) are applied to indicator values based on the different distributions between control and conflict groups. There are five 'bins' of ratings values (0-20, 20-40, 40-60, 60-80, 80-100). The dotted lines show how the quartiles of indicator values translate to the thresholds of those bins.

[19] These distributions of values are derived from our statistical analysis of tenure risk, available here.

The idea is to ensure that:

- values less than the first, lowest quartile of the places where tenure disputes did *not* occur get a rating less than 20;
- values larger than the third quartile of the places where disputes *did* occur get a rating larger than 80; and
- values in the second and third quartiles are distributed evenly using linear interpolation.

Within each rating bin – e.g. between 0 and 20 – indicator values are distributed evenly. So in the example in figure 1, if the range of values in that bin is from 0 to ~2, a value in the middle of that distribution (i.e. 1) would get a rating of 10. And a value of 1.5 (halfway between 1 and 2) would get a rating of 15, and so on.

Our testing found that using five ratings bins gave optimal predictive power to the model. With greater than five, the accuracy of the rating (as shown by the difference in rating between control and conflict locations) did not significantly change. But with fewer than five, the differences in ratings started to become less reliable.

We applied this approach to each sub-national indicator used in the model where there was a proven association with tenure risk. For national-level indicators, we applied a similar, but not identical approach, whereby the distributions of indicator values were divided into scoring bins according to each indicator's association with tenure disputes.

This difference in approach was a result of the different analyses we applied to the national-level indicators, in which we just looked at indicator values in countries where disputes had occurred. Because there was no 'control' group of indicator values for the national level indicators, we used the distribution of values in conflict countries in comparison to the entire range of possible values to provide the ratings bins. We then linearly interpolated values to ratings between the thresholds for each bin as with the sub-national indicators.

Relative regional weighting

We needed to process the indicator scores to reflect the variable quality and consistency of the raw data that goes into them. For example, while the MPI indicators that we use may be theoretically globally consistent and comparable, there will be some differences in the way that the underlying data is collected and reported from country to country.

To account for this issue, the combined score is weighted according to the region it is in. Each country has a relative similarity weight, which describes how high the ratings are, on average across the whole country, in comparison to the regional (Africa, Asia, Latin America) average. By combining the queried location's combined Indicator Scores with its country's relative risk weight, we calculate the relative regional weighted indicator scores.

Relative similarity rating

The Relative Similarity Rating combines the 14 weighted indicator scores, to provide a single rating that reflects the range of key factors that influence tenure disputes

The indicator selection process provides a list of n ESG indicators that can be used to model similarity to tenure dispute locations. The overall similarity rating, S, for a location is calculated as a weighted sum:

$$S = B_c + A_c\left(\sum_{i=1}^{n} w_i x_i\right)$$

Where $(w_i)_{i=1}^{n} \in [0,1]$ are fixed weights that sum to 1, A_c and $B_c$are coeffients depending on the region, chosen, by linear interpolation, to reflect the score relative to the region and $(x_i)_{i=1}^{n} \in [0,100]$ are the indicator scores for each identified ESG indicator at the location.

Because the importance of tenure risk to each contextual factor is already accounted for in the weighting of each indicator, the weights of each indicator in Landscope v4.2 are provided equally. This prevents national-level indictors, or factors for which there is a greater availability of data (such as poverty), from dominating the model excessively.

Each indicator score is therefore given a weight of 1/14 (0.07142857) in the model, with the resulting ratings summed to provide a combined similarity rating.

Context factor rating

Landscope then groups indicators into three baskets – Local Conditions, National Conditions, and Local Behavior – and produces a rating for each basket. The overall ratings for these groups are a mean average of the weighted indicator scores in each.

Overall Similarity classifications

Landscope combines Context Factor Rating and Relative Similarity Rating for the queried location to arrive at one of five possible characterizations of the queried location. The specific criteria for each Overall Similarity classification are based on TMP Systems' extensive experience in providing in-depth analysis of tenure disputes, and extensive testing of how different levels of Relative Similarity Ratings and Context Factor Ratings align with on-the-ground realities in the places where those disputes happen.

Landscope's software includes a set of calculations that determine which of the mutually exclusive Overall Similarity categories the location belongs to. The summaries below provide a summary of the classifications, and the logic behind these calculations:

Highly Similar, where the data profile is extremely similar to places where tenure has occurred in the past, both in terms of the Relative Similarity Rating and at least two Context Factor Ratings. A location is classified as Highly Similar if:

- at least two of the Context Factors are rated 70 or above, and
- the Relative Similarity Rating is 75 or above, and
- at least half of the indicators are present.

Similar, when there is a broad similarity between the data profile and places where tenure disputes have occurred, but overall Similarity Ratings are not very high. A location is classified as Similar if:

- the data do not meet the criteria for Highly Similar, and

- at least two of the Context Factors are rated 60 or above, and
- Relative Similarity Rating is 65 or above, and
- at least half of the indicators are present.

Partially Similar, where one or two Context Factors are significantly similar to places where tenure disputes have occurred. A location is classified as Partially Similar if:

- the data do not meet the criteria for Highly Similar or Similar, and
- one Context Factor is rated 60 or above or at least two Context Factors are rated 50 or above, and
- at least half of the indicators are present.

Dissimilar, where the data profile is very different from places where tenure disputes have occurred. A location is classified as Dissimilar if:

- the data do not meet the criteria for Highly Similar, Similar, or Partially Similar and
- no Context Factors is rated higher than 35, and
- at least half of the indicators are present.

Inconclusive, where the data profile is not clear enough for Landscope to provide a reliable conclusion.[20] A location is classified as Inconclusive if:

- the data do not meet the criteria for Highly Similar, Similar, Partially Similar or Dissimilar and
- at least half of the indicators are present.

Other outputs

Landscope supports the Overall Similarity classification with a series of additional outputs to help the user understand and manage tenure risk:

- Similarity Ratings for the three Context Factor groups
- Guidance for users on how to deal with the specific issues identified in the area,
- Alerts of particularly problematic ESG issues
- Map showing additional information such as protected areas and population density
- Charts displaying discrete indicator ratings in comparison with regional averages

20 In some instances, where the underlying datasets do not cover the area selected by the user and Landscope lacks sufficient indicator data to make a reliable assessment, the website will return an 'Insufficient Data' summary.

5. Conclusion and next steps

Tenure risk is still an emerging area of study, and as such the methodology used for Landscope 4.2 is likely to improve in future versions, as new data becomes available and our understanding of tenure risk deepens.

The system we have developed uses the most comprehensive available information, and an empirical process to translate the intuitive understanding that we have developed into a simple, quantitative approach to better understanding tenure risk.

We do not assert that Landscope is a perfect product. And because we are releasing it for general use free of charge, we have a real interest in improving it. If you see something wrong – or even if you receive a result you just don't agree with – we want to know right away. For more information on Landscope, or to provide feedback on this document, please email landscope@tmpsystems.net.

Appendix 1: Indicator details

National conditions

The Corruption Perceptions Index

Description: The Corruption Perceptions Index scores how corrupt public sectors are seen to be, as determined by expert assessments and opinion surveys.

Provider: Transparency International

Indicators used in the model:
Corruption
This indicator is based on the Corruption Perceptions Index score. The CPI score rates countries on a scale from 0 (more corrupt) to 100 (less corrupt), and is based on 16 different surveys and assessments from 12 institutions. A country must have been evaluated by at least three sources to appear in the CPI.

Human Development Index

Description: The Human Development Index (HDI) is a composite index focusing on three basic dimensions of human development: the ability to lead a long and healthy life, measured by life expectancy at birth; the ability to acquire knowledge, measured by mean years of schooling and expected years of schooling; and the ability to achieve a decent standard of living, measured by gross national income per capita.

Provider: United Nations Development Program

Indicators used in the model:

- Human Development Index

  The HDI score is a composite index, ranging from 0-1, based on life expectancy, education and per capita income. A country scores a higher HDI when lifespans, education levels and the GNI (PPP) per capita levels are higher.

Worldwide Governance Indicators

Description: The Worldwide Governance Indicators (WGI) project reports aggregate and individual governance indicators for over 200 countries and territories over the period 1996–2017, for six dimensions of governance: Voice and Accountability, Political Stability and Absence of Violence, Government Effectiveness, Regulatory Quality, Rule of Law, and Control of Corruption.

Provider: Natural Resource Governance Institute (NRGI), World Bank Development Research Group

Indicators used in the model:

- Political Stability

- This indicator measures political instability and/or politically motivated violence, including terrorism.
- Regulatory Quality
- This indicator measures the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.

Local conditions

Multidimensional Poverty Index (MPI)

Description: The global Multidimensional Poverty Index (MPI) is an international measure of acute poverty covering 105 countries. It complements traditional income-based poverty measures by capturing the severe deprivations that each person faces at the same time with respect to education, health and living standards.

Provider: Oxford Poverty and Human Development Initiative (OPHI), Oxford Department of International Development

Indicators used in the model:

- Relative Poverty (local MPI value / national MPI value)
- Relative poverty measures the ratio of the local level of poverty to the national level, using the overall MPI values for the user's location and the national average. The MPI is a combined measure of the proportion of people in multidimensional poverty, and the intensity of the poverty they experience.
- Vulnerability to Poverty
- This metric measures the proportion of people deprived in 20-33% of the ten component dimensions of Multidimensional Poverty (.
- Child School Attendance
- This indicator measures the proportion of poor households in which any school-aged child is not attending school up to the age at which they would complete class 8.
- Access to Electricity
- This indicator measures the number of poor households without access to electricity.
- Asset Ownership
- This indicator measures the number of households that do not own more than one radio, TV, motorbike and refrigerator and does not own a car or truck.

Georeferenced Ethnic Power Relations (GeoEPR) and Ethnic Power Relations (EPR)

Description: This dataset combines the GeoEPR dataset (which geo-codes politically relevant ethnic groups) and the Ethnic Power Relations (EPR) Core Dataset 2018 (which identifies all politically relevant ethnic groups and their access to state power in every country of the world from 1946 to 2017). It includes annual data on over 800 groups and codes the degree to which their representatives held executive-level state power—from total control of the government to overt political discrimination.

Provider: ETH Zurich - International Conflict Research

Indicators used in the model:

- Access to Power
- This indicator measures the percentage of all ethnic groups in the area that have access to central state power. Groups described as Junior Partner, Senior Partner or Monopoly are classed as having access, while groups described as Excluded, Irrelevant, or Discriminated are classed as not having access (groups described as self-excluding are classed in a third group).

World Database on Protected Areas

Description: The World Database on Protected Areas (WDPA) is the most comprehensive global database on terrestrial and marine protected areas.

Provider: United Nations Environment Program (UNEP) and the International Union for Conservation of Nature (IUCN)

Indicators used in the model:

- Protected Areas
- This indicator shows the proportion of the buffer zone covered by some kind of protected area designation (such as national parks or conservation zones), as a percentage of the buffer zone.

Local behavior

GlobCover (versions 2.2 and 2.3)

Description: The GlobCover v2.2 Land Cover map provides values for the period December 2004 - June 2006. The map is derived by an automatic and regionally-tuned classification of a MERIS FR time series. It classifies all land as one of 22 land cover classes, which are defined with the UN Land Cover Classification System (LCCS). GlobCover v2.3 provides a comparable set of values for the year 2009.

Provider: European Space Agency, in partnership with JRC, EEA, FAO, UNEP, GOFC-GOLD and IGBP.

Indicators used in the model:

- Land Use Change

- This indicator provides the total change in land use categories in the area from 2005/2006 to 2009, expressed as a percentage of the total number of cells in the buffer area.

Gridded Population of the World v4

Description: The Gridded Population of the World, Version 4 (GPWv4) consists of estimates of human population (number of persons per pixel), consistent with national censuses and population registers, for the years 2000, 2005, 2010, 2015, and 2020. It models the distribution of human population on a continuous global raster surface.

Provider: Socioeconomic Data and Applications Center (SEDAC)/Center for International Earth Science Information Network (CIESIN)

Indicators used in the model:

- Population Change
- Percentage population change in the Area of Interest, based on the Gridded Population of the World's estimates for 2015-2005.

Appendix 2: Basis for buffer zones

Landscope requires users enter a sector associated with their location of interest. These sectors each have different buffer sizes, based on the typical land requirements of projects in that sector, as described below.

Agribusiness

Buffer radius: 60 km

Buffer area: 11,309.73 km^2

Typical land footprint: Agricultural projects typically have a large requirement for land, as they require a large area for growing the crops to sustain an industrial agribusiness operation. In palm oil plantations, for example – a highly efficient crop in terms of land use – a mill will commonly source oil palm from up to 60km away.

Infrastructure

Buffer radius: 50 km

Buffer area: 7,853.98 km^2

Typical land footprint: Infrastructure projects comprise a diverse group of project types and related sectors, and thus vary widely in their impact on and requirements for land. We use a 50km radius for infrastructure projects because the area covered by this buffer zone provides a good sense of the prevailing local conditions which affect tenure disputes over infrastructure projects. Likewise, infrastructure project impacts often affect people and natural resources in this zone.

Hydropower

Buffer radius: 60km

Buffer area: 11,309.73km^2

Typical land footprint: Hydropower projects have a large variety of impacts on land, but the ones that have the greatest potential for disputes over tenure are typically those with a larger land footprint. Direct displacement – the most common driver of tenure disputes – is most common within 60km of a hydropower project, often as a result of the filling of a large reservoir above the dam installation. Larger reservoirs do occur, although they are relatively uncommon, but smaller dam reservoirs may also have economic impacts as far as 60km downstream as a result of changes in water supply and riverine resources like fish.

Manufacturing / Processing

Buffer radius: 25 km

Buffer area: 1,963.50 km^2

Typical land footprint: The direct land requirement of manufacturing or processing facilities can often be fairly small, but they often require raw materials that must be sourced from the vicinity. The buffer area reflects the fact that negative impacts from industrial processing or manufacturing plants are typically most severely felt in a relatively small area around the facility (such as from pollutants released into a water source), and non-agricultural processing sites are typically situated relatively close to the raw materials they use (such as near a quarry for aggregate production).

Energy

Buffer radius: 25 km

Buffer area: 1,963.50 km^2

Typical land footprint: This sector covers projects that produce energy from a variety of sources (excluding hydropower). Land requirements for these projects vary depending on the type of input used for energy production, and the scale of the project, but projects that trigger tenure disputes very rarely have very large direct land requirements. Impacts from energy production processes or site construction, however, may impact inhabitants of the local area tens of kkilometers away from the heart of the installation.

