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Generalized method to estimate value of urban assets for natural disaster risk assessment at the macro scale

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Abstract:

Natural disasters can have a damaging effect on human society. To understand the magnitude of risk of a natural disaster at the macro scale, basic socioeconomic parameters such as population or gross domestic product (GDP) are often used as proxies to evaluate value of specific asset classes (e.g., urban assets, agricultural land, etc.). However, such information is not always available and it becomes a challenge to perform cost-benefit analysis of tailored strategies to protect an asset class from natural disaster risk. Recent studies showed the prospects of relating GDP and population to produced capital representing urban assets. However, the methods used in earlier studies are unclear and resulted in different outcomes that need further clarification and generalization. This study aims to demonstrate the potential of developing a more generalized method to characterize the relation between produced capital and basic socioeconomic parameters at the global scale. We include purchasing power parity (PPP) into the country GDP and produced capital data, respectively. We develop a more generalized method that incorporates the uncertainty range to quantify the produced capital. This is an improvement from previous studies. The new approach might be useful for macro scale risk assessment within the context of climate change.

KEYWORDS natural disaster; risk; socioeconomic; produced capital; GDP

INTRODUCTION

Risk assessment due to natural disasters (such as flood, drought, tropical cyclone, bushfire) is essential for developing policies and strategies (e.g., infrastructure upgrading, evacuation procedures) to protect lives and wealth. At the macro scales (i.e., country, regional and global scales), the socioeconomic parameters used for risk analysis are often limited to population and gross domestic product (GDP) information. This is probably because access to detailed information (e.g., urban assets, agricultural land, pastureland, etc.) is only available to a handful of countries or regions. For example, the data of value of various asset classes ("Wealth of Nations" at the World Bank, see details in DATA AND METHODS section) is limited to somewhere between two-thirds to three quarters of all countries at the global scale. Due to data scarcity, it is a challenge to perform risk assessment for targeted asset classes. It is important to have a reliable asset value estimation method because it is the first step towards cost-benefit assessment of tailored strategies to protect an asset class (e.g., urban assets, agricultural land, pastureland, etc.) from natural disaster risk (particularly hydrological extreme events under climate change).

Among these asset classes, previous studies demonstrated the prospects of relating basic socioeconomic parameters (i.e., population, GDP) to the value of urban assets related to hydrological extremes (e.g., Nicholls *et al.*, 2008; Hallegatte *et al.*, 2013; Winsemius *et al.*, 2013). These studies found that the ratio of produced capital (representing urban assets that includes buildings, factories, ports, roads, machineries, equipment; see UNU-IHDP and UNEP, 2012) per capita to GDP per capita ranges from 1 to 5. However, these results are not generalized and it is not clear (to us) which ratio we should apply for risk assessment within the context of hydrological extremes and climate change; and that can make a significant difference to the end results.

The objective of this study is to investigate the potential of developing a more generalized approach to characterize the relationship between an asset class (here, we use produced capital) and basic socioeconomic parameters (i.e., population, GDP) at the global scale. We apply a statistical method to quantify the uncertainties and incorporate it into our model. To address the bias due to differences in purchasing power among the countries, we incorporate the purchasing power parity (PPP) into the GDP data and asset class for each country. We describe the formulations of this analysis in the FORMULATION section; datasets and methodologies in the DATA AND METHODS section; and results and how they relate to previous studies in the RESULTS AND DISCUSSION section. We summarize our findings and future tasks in the SUMMARY section.

FORMULATION

Similar to Hallegatte *et al.* (2013), we first assume a first order regression relationship between PPP-adjusted produced capital per capita (denoted as y) and PPP-adjusted GDP per capita (denoted by *GDP pcap*),

$$y = a \times GDP\ pcap \tag{1}$$

where a is a constant. For a number of samples (i = 1, 2, ..., n), the best-fit a in Equation (1) is optimized between observations $(y)_{i,obs}$ and modelled results $(y)_{i,model}$ using the least-

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squares method,

$$SSE_{pro} = \sum_{i=1}^{n} \left[(y)_{i,obs} - (y)_{i,model} \right]^2 \quad (2)$$

where SSE_{pro} is the sum of squared error of the regression model of PPP-adjusted produced capital per capita.

From above (Equation 2), we calculate an unbiased estimator for the standard deviation of error term in the model (s_{pro}) as

$$s_{pro} = \sqrt{SSE_{pro} / (n - m)} \quad (3)$$

where m is the number of constants in a regression model. For Equation (1) (with only one constant), we set $m = 1$. The standard deviation could form part of the prediction interval (Navidi, 2010; Wackerly *et al.*, 2008). From s_{pro} (Equation 3), we estimate the standard deviation of the prediction error ($s_{pred,pro}$) as

$$s_{pred,pro} = s_{pro} \sqrt{1 + \frac{1}{n} + \frac{\left(GDP\,pcap - \overline{GDP\,pcap}\right)^2}{\sum_{i=1}^{n} \left(GDP\,pcap_i - \overline{GDP\,pcap}\right)^2}} \quad (4)$$

From Equation (4), we could estimate a prediction interval that forms part of the regression model (i.e., Equation 1). Based on Equations (1) and (4), $100(1 - \alpha)\%$ prediction bands (where probability $(1 - \alpha)$ is the confidence coefficient) is calculated as

$$y_{model+pred} = a \times GDP\,pcap \pm t_{n-m,\alpha/2} \times s_{pred,pro} \quad (5)$$

where $t_{n-m,\alpha/2}$ is the point on the Student's t curve with $(n - m)$ degrees of freedom that cuts off an area of $\alpha/2$ in the right-hand tail. We evaluate the results of Equation (5) in characterizing the relationship between PPP-adjusted produced capital per capita and PPP-adjusted GDP per capita in the RESULTS AND DISCUSSION section.

DATA AND METHODS

We downloaded the population, GDP (in 2005 USD) and purchasing power parity to market exchange rates (PPP/MER) conversion ratio that are publicly accessible from the World Bank (2014a, 2014b). All the data span across the period 1960–2010. In this analysis, we used GDP data in 1995, 2000 and 2005. To address the bias issue in the GDP data, we use the GDP and PPP/MER conversion ratio to calculate the PPP-adjusted GDP (i.e., in 2005 USD PPP). We also downloaded the "Wealth of Nations" that contains the value of different asset classes (e.g., produced capital) for each country in 1995, 2000 and 2005 (in 2005 USD) from the same source. Using the PPP/MER conversion ratio (above), we calculated the PPP-adjusted value of the produced capital per capita (i.e., in 2005 USD PPP). From there, we separated the PPP-adjusted value of produced capital into two independent subsets (both consist of country-based population, PPP-adjusted GDP, produced capital). The first subset contains the data in all 1995, 2000 and 2005 (360 samples). The second subset covers the remaining data which is less complete (compared to the first subset) in terms of data availability. It only contains the data in some years in all 1995, 2000 and 2005 (55 samples). We used the first subset for parameterization of our model in Equation (1) and an estimate of the standard deviation of the prediction error in Equation (5). We used the second subset for model valida-

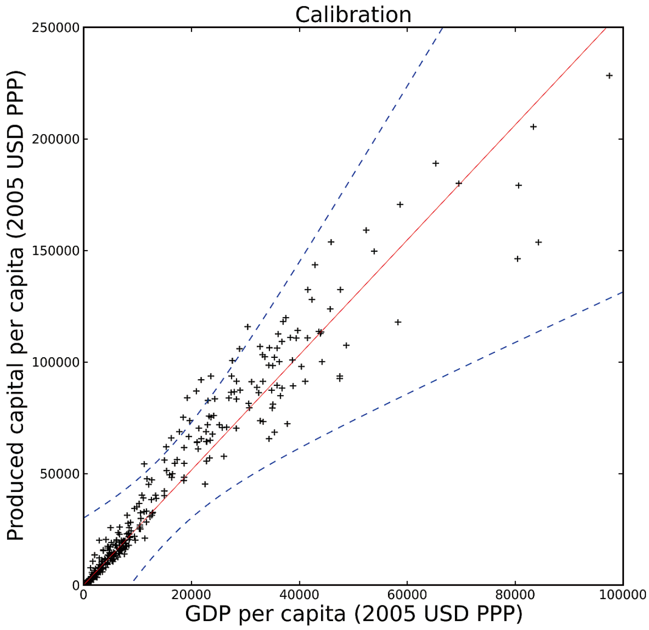

Figure 1. Comparison of produced capital per capita-GDP per capita relationship between the data and the final model (Equation 5) with a prediction interval of 90% for the calibration subset data (360 samples). Equation (1) is in red and Equation (5) is in dotted blue

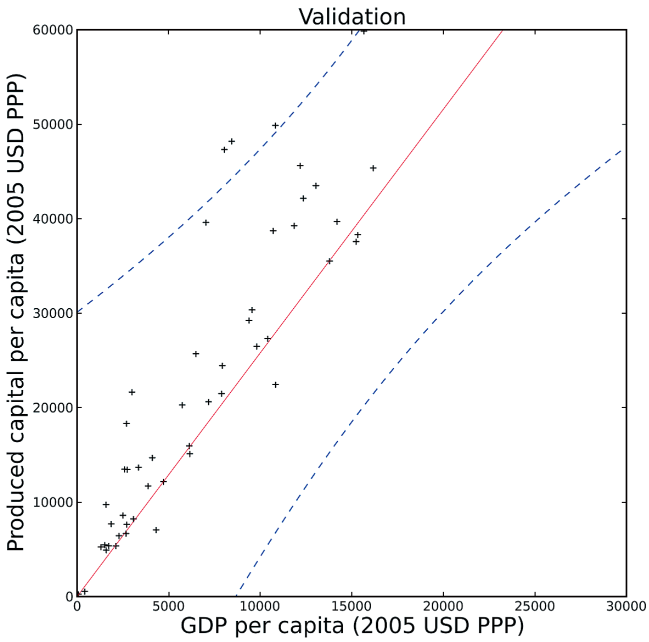

Figure 2. Comparison of produced capital per capita-GDP per capita relationship between the data and the final model (Equation 5) with a prediction interval of 90% for the validation subset data (55 samples). Equation (1) is in red and Equation (5) is in dotted blue

tion (at a confidence coefficient of 0.9 or prediction interval of 90%) and evaluated the performance of Equation (5) (see details in the RESULTS AND DISCUSSION section).

RESULTS AND DISCUSSION

The parameterization showed that the best-fit constant is a = 2.58 (Equation 1) and the standard deviation of error term in the model (s_{pro}) is 12226.3 (2005 USD PPP). Hallegate *et al.* (2013) showed a = 2.8 without any mention of the data set. By setting the prediction interval at 90%, the model (i.e., Equation 5) covers 96.11% of the calibration data (346 out of 360 points) (Figure 1). Similarly, we found that the model covers 90.91% of the calibration data (50 out of 55 points) in the validation data (Figure 2). The results reflect the robustness of the model in estimating the approximate value of produced capital for each country at the global scale.

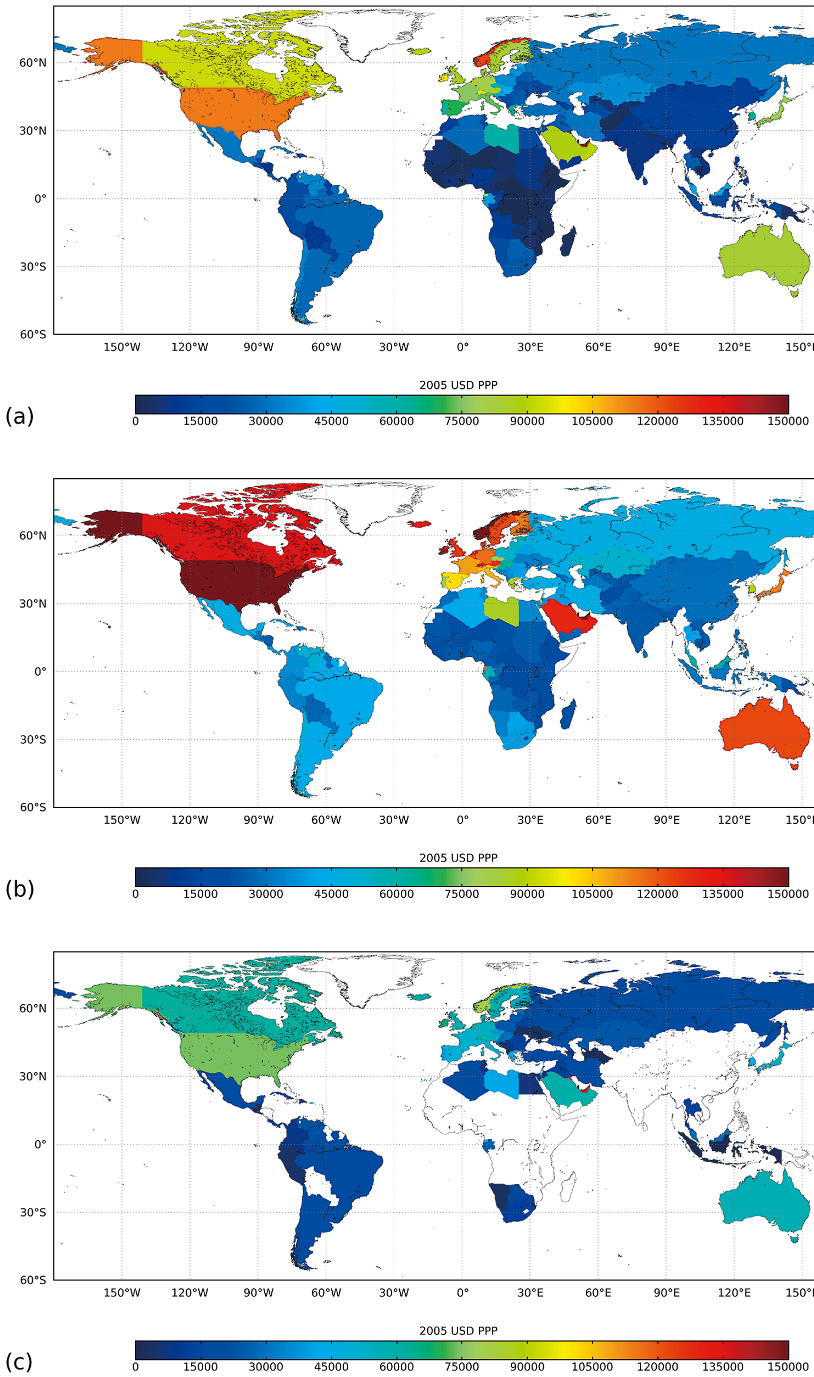

Figure 3. Global maps with estimated produced capital per capita for each country at a prediction interval of 90% using Equation (5): (a) mean, (b) upper limit and (c) lower limit. When the lower limit estimates of a country becomes negative (Equation 5), we set it to zero (e.g., some countries in South America, Africa, Asia). Data is not available for French Guiana, Greenland, Myanmar, North Korea, Somalia, Taiwan, Western Sahara and the ocean. Both are displayed in white color

A few studies have investigated the empirical relationship between produced capital per capita and GDP per capita. In those studies, the constant "*a*" (similar to Equation (1) here) were estimated to range from 1 to 5 (Winsemius *et al.*, 2013; Nicholls *et al.*, 2008; Hallegatte *et al.*, 2013). Our results consider the PPP-adjusted GDP and get the constant (2.58) that is within the range of the earlier studies. However, we are not convinced that a single global constant "*a*" (Equation 1) would adequately represent that of all countries because the socioeconomic parameters (e.g., population, GDP, produced capital) varies from country-to-country and year-to-year. In this respect, the inclusion of the statistically-justified range of uncertainty enables us to consider a wider range of results (Figure 2). For instance, our current calculations give ratios of produced capital per capita to GDP per capita that range from ~1.3 to ~4.3 for a GDP per capita of 10000 (2005 USD PPP). This ratio would range from ~1.5 to ~4.2 for a GDP per capita of 50000 (2005 USD PPP). These ranges are quite stable and are consistent with earlier reports (Winsemius *et al.*, 2013; Nicholls *et al.*, 2008; Hallegatte *et al.*, 2013). Similar to the application of the spatial map of basic socioeconomic parameters (i.e., population, GDP), we show the results on a global map (Figure 3). Estimated results using Equation (1) (Figure 3a) show a distinctive difference in produced capital per capita between rich developed countries (e.g., Northern and Western Europe, North America, some oil-rich Middle Eastern countries, Japan, Oceania) and relatively poor developing countries (e.g., the majority of Asia, South America, Eastern Europe). It is consistent with the general expectation of positive correlation between GDP and urban asset values noted in earlier studies. We note that the prediction range widens as the GDP per capita become much higher (for instance, >60000 (2005 USD PPP) in Figure 1). It reflects the outcomes of the underlying statistical structure (see FORMULATION section); and it is premature to conclude further from there because we have limited country samples with very high GDP per capita. The methodology is worthy of further validation when more country samples become available in the future. When such information (produced capital in this study) is not available, this methodology could be used for identification of the possible range (Figures 3b and 3c; at a prediction interval of 90%) and hence as (first step) proxies for natural hazard risk assessment.

SUMMARY

A reliable estimate of the value of an asset class might assist natural disaster risk assessment at the macro scale. We showed that it is possible to come up with a mathematical approach to relate the basic socioeconomic parameters to an asset class (i.e., produced capital). The new model (Equation 5) is able to give robust estimates of the asset value (Figures 1 and 2). The ratios of produced capital per capita to GDP per capita (see the RESULTS AND DISCUSSION section) are consistent with the range suggested by previous studies and this range is statistically-justified with the choice of prediction interval (Equation 5). In a sense, the new approach can be perceived as a framework that explains all the different outcomes of previous studies (i.e., ratio of produced capital per capita to GDP per capita that ranges from 1 to 5, Nicholls *et al.*, 2008; Hallegatte *et al.*, 2013; Winsemius *et al.*, 2013). In this respect, this approach is an improvement and more general than the previous studies. It is possible to extend this mathematical approach to estimate the value of other asset classes, such as agricultural land, pastureland or others. It could be a first step towards development of suitable strategies to protect the targeted asset classes for different natural disasters within the context of hydrological extremes and climate change (and possibly beyond).

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