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We Lose Ground:
Global Assessment of Land Subsidence Impact Extent

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Abstract: Depletion of groundwater aquifers along with all of the associated quality and quantity problems which affect profitability of direct agricultural and urban users and linked groundwater-ecosystems have been recognized globally. During recent years, attention has been devoted to land subsidence—the loss of land elevation that occurs in areas with certain geological characteristics associated with aquifer exploitation. Despite the large socioeconomic impacts of land subsidence most of these effects are still not well analyzed and not properly recognized and quantified globally. In this paper we developed a land subsidence extent index (LSIE) that is based on 10 land subsidence attributes, and applied it to 113 sites located around the world with reported land subsidence effects. We used statistical means to map physical, human, and policy variables to the regions affected by land subsidence and quantified their impact on the index. Our main findings suggest that LSIE increases between 0.01 and 5% by changes in natural processes, regulatory policy interventions, and groundwater usage while holding all other variables unchanged. Effectiveness of regulatory policy interventions vary depending on the lithology of the aquifer system, in particular its stiffness. Our findings suggest also that developing countries are more prone to land subsidence due to lower performance of their water governance and institutions.

Keywords: aquifer overdraft; water scarcity; groundwater pumping regulations; impacts; policy effectiveness; land subsidence extent index

JEL Classification: Q25, Q56.

We Lose Ground:

Global Assessment of Land Subsidence Extent and its Causes

Abstract: Depletion of groundwater aquifers along with all of the associated quality and quantity problems which affect profitability of direct agricultural and urban users and linked groundwater-ecosystems have been recognized globally. During recent years, attention has been devoted to land subsidence—the loss of land elevation that occurs in areas with certain geological characteristics associated with aquifer exploitation. Despite the large socioeconomic impacts of land subsidence most of these effects are still not well analyzed and not properly recognized and quantified globally. In this paper we developed a land subsidence extent index (LSIE) that is based on 10 land subsidence attributes, and applied it to 113 sites located around the world with reported land subsidence effects. We used statistical means to map physical, human, and policy variables to the regions affected by land subsidence and quantified their impact on the index. Our main findings suggest that LSIE increases between 0.01 and 5% by changes in natural processes, regulatory policy interventions, and groundwater usage while holding all other variables unchanged. Effectiveness of regulatory policy interventions vary depending on the lithology of the aquifer system, in particular its stiffness. Our findings suggest also that developing countries are more prone to land subsidence due to lower performance of their water governance and institutions.

1. Introduction

Land subsidence (LS), defined as the settlement of the land surface, is generated by human-induced and natural-driven processes, including natural compaction of unconsolidated deposits (Zoccarato et al., 2018), and human activities such as subsurface water mining, or extraction of oil and gas (Gambolati et al., 2005). LS is a global problem (Galloway et al., 2016; Herrera-Garcia et al., 2021; Kok and Costa, 2021), mostly studied and recognized, to different extents, in association with aquifer overexploitation (which is the focus of this paper). LS occurrence around the world is most prominent in those aquifer systems composed of loose unconsolidated materials (e.g., sands, clays, and silts) that are over-pumped (e.g., Poland, 1984; Tomás et al., 2005; Gambolati and Teatini, 2015; Bonì et al., 2015).

Climate change impacts on water availability and population growth are expected to increase competition for water, leading to extensive groundwater withdrawals. The expected overexploitation of aquifers will exacerbate current and future damage from various LS impacts. LS causes significant damages to local communities and to the environment (Yoo and Perrings, 2017; Teatini et al., 2018). As such, identifying the types of damages and quantifying them in terms of the various physical impacts and their short- and long-term economic costs would be an essential first step for preparing policies to address this problem. However, most studies on LS are indicative in the sense that they identify the driving processes and measure the physical effects of LS in specific localities. Few are the works that assess the global impacts of LS in terms of social, environmental, and/or economic consequences.

A review of existing literature suggests that LS can cause the following impacts (e.g., Poland, 1984; Holzer and Galloway, 2005; Lixin et al., 2010; Bru et al., 2013; Erkens et al., 2016), as summarized in Dinar et al. (2020): (1) Socio-economic impacts, such as structural damages (Bru et al., 2013); (2) Environmental damages, such as malfunctioning of drainage systems (Viets et al., 1979); (3) Geological-related damages that affect underground lateral water flows (Poland, 1984); (4) Environmental damages, such as reduced performance of hydrological systems (Poland, 1984); (5) Environmental damages, such as wider expansion of flooded areas (Poland, 1984); (6) Hydrogeological damages that result in groundwater storage loss (Holzer and Galloway, 2005; Béjar et al. 2017); (7) Impact on adaptation ability to climate change (such as the loss of the buffer value of groundwater in years of scarcity) Erkens et al., 2016; (8) Groundwater contamination, such as seawater intrusion resulting in decrease of farmland productivity in coastal aquifer systems and decrease of fresh-water availability (Holzer and Galloway, 2005; Poland, 1984); (9) Loss of high-value transitional areas (e.g., saltmarshes) (Viets et al, 1979); and (10) Shift of land use to poorer activities (e.g., from urbanized zones to rice fields, from rice fields to fish and shellfish farms, from fish farms to wastewater ponds) (Heri et al., 2018). A summary of the literature used for the ten LS attributes and their impacts is summarized in Appendix A (Table A1).

Estimates of economic damages from land subsidence are not yet widely available, and most of the published studies on this phenomenon focus on a physical quantification of subsidence and on cataloguing the damages (Borchers and Carpenter, 2014). Few works have assessed local LS damages (e.g., Jones and Larson, 1975; Warren et al., 1975; Lixin et al., 2010; Tomás et al., 2012; Sanabria et al., 2014; Yoo and Perrings, 2017; Wade et al., 2018; and Díaz et al., 2018).

Selected damages cited in the literature range from $756 million in the Santa Clara Valley of California (Borchers and Carpenter, 2014), to $1.3 billion in the San Joaquin Valley of California between 1955 and 1972, in 2013 dollars, to $18.03 billion in the Tianjin metropolitan area in the period up to 2007 (Lixin et al., 2010). It is worth noting that, since the studies leading to these estimates use different approaches, refer to different sizes of affected regions, and span over different periods of time, one should not attempt to compare the values but rather use them as indicative only. A recent study (Kok and Costa, 2021) enumerates the various types of costs associated with LS and suggests a standardize economic framework for their cost evaluation.

In a recent publication, Herrera-Garcia et al. (2021) identified 200 locations (mostly urban) in 34 countries that experienced LS during the past century. However, these authors also indicate that the LS extent is known only in one third of these locations. Given lack of direct data on damages, Herrera-Garcia et al. (2021) use what they define as the exposure to potential land subsidence (PLS) and focus on areas where the probability for potential subsidence is high. Their calculations suggest that PLS affects 8 percent of the global land surface, and that 2.2 million square kilometers of global land is exposed to high to very high probability for PLS, affecting 1.2 billion urban inhabitants and threatening nearly US$ 8.2 trillion GDP. This estimate on the global economic exposure could be a lower-level estimate because the authors assumed that the GDP per capita is homogenous within each country, not taking into account the geographical variations in productivity, for example between different regions within a country, or between cities and rural areas. However, this economic estimate on the global subsidence exposure does not directly translate to subsidence impact or damages. The lack of information on the cost of damages caused by current and historical subsidence worldwide, prevents these authors from evaluating the impact of global land subsidence.

Realizing the need for a global assessment of LS impacts and the present difficulty to provide global economic quantification for those effects (Kok and Costa (2021), Herrera-Garcia et al. (2021)), this paper has taken an approach of quantitatively (not economically) assessing global LS impact extents and their determinants. We start with a meta-analysis and review of relevant literature on LS occurrence and physical quantification of its impacts in various sites around the world. In the absence of economic value for the LS-induced damage, we develop an index to assess the LS impact extent (LSIE), using the classification of the 10 LS impacts listed above. This assessment allows us to identify different types of impacts in different locations and is used to explain the effects of physical, regulatory, and population conditions on LSIE. Such conditions include aquifer lithology, managing institutions, social systems, existing policies, population pressure, water-level depletion from over-pumping, and several others.

From here on the paper develops as follows: Section 2 explains the principles used to develop the LSIE index. We then present in Section 3 an empirical investigation into the social, physical and institutional determinants most likely affecting land subsidence and its impact as measured by LSIE. Section 4 presents the data-collection process, the variables constructed, and the hypotheses regarding their effects on LSIE. This is followed in Section 5 by the empirical specifications of our models and the derived hypotheses. Section 6 includes results from the LSIE global distribution, and results from the statistical analysis. The results are followed by policy simulations in Section 6, with estimates of the marginal impact of policy variables on the extent of the LSIE. Discussion on the policy results is provided in Section 7. In Section 8 we present our conclusions and policy implications.

2. The LS Impact Extent (LSIE) Index

Use of indicative indexes to assess environmental health status has been practiced by many national and international agencies (OECD, 2003; EEA—Gabrielsen and Bosch, 2003; EPA—Fiksel et al, 2012). Use of indexes allows comparison across states and geographical regions (OECD, 2003). As explained below, we developed an indicative index to measure LS impact extent in the locations of the dataset we compiled.

Due to the heterogeneous and partial nature of the information we extracted from all reviewed LS studies, and following the earlier discussion on the difficulties in comparing the extent of impacts within an LS site and across LS sites, we adopted and adapted the Qualitative Structural Approach for Ranking (QUASAR) method, as explained in Galassi and Levarlet (2017). QUASAR allows to compile the various impacts of LS identified in a given location into one index. A review of approaches to assess non-continuous impacts of human intervention on the environment can be found in Purvis and Dinar (2020). We follow Purvis and Dinar (2020), who apply a similar scoring method to indicate various effects of inter- and intra-basin water transfers on basin welfare.

Our assessment model was developed as follows: We conducted an exhaustive review (details are provided below) of related literature that indicate different types of land subsidence impacts.

During the review of the literature we identified impacts that were discussed by the authors of the publications. Each LS reviewed was associated with up to N impacts (we identified N=10 in the papers reviewed). We identified several publications referring to the same LS site. Some of them included subsets of the N LS attributes. For example, if we had 2 sources for the same location with LS issues and one source reported the existence of LS attributes 3, 5, 6 and the second source for the same location reported the existence of LS attributes 2, and 4, then we assigned this location as having LS attributes 2, 3, 4, 5, 6. Therefore, in these cases we combined the LS attributes from the various reports. Because no quantitative measurement was provided, we just marked whether or not an impact is mentioned in a publication with a value of 0 or 1 (No/Yes). Let S be the set of sites with LS impacts that we identified, and let A_{si} be LS impact i, $i = 1, \dots , N$ in site s, s=1,…, S.

Then:

$$A_{si} = \begin{cases} 0 \quad if \text{ LS impact } i \text{ has no effect on site } s \\ 1 \quad if \text{ LS impact } i \text{ has any effect on site } s \end{cases} \quad \forall\, i = 1, \dots, N; s = 1, \dots, S \qquad [1]$$

Then the total net effect (NE) of LS (the composite impact) in a given site s is the sum of the number of LSIE attributes that affect a given site:

$$NE_s = \sum_{i=1}^{N} A_{si}, \qquad [2]$$

with NE being an integer. Given the nature of the A_{si}'s we can expect that $0 < NE_s \leq N$. Then the *LSIE* is defined as:

$LSEI_s$=NE_s/N, where $0 < LSEI_s \leq 1$. [3]

It is assumed that the more LS impact types (coined later in the paper as 'attributes') are identified in a site, the larger the overall impact of LS. It should be mentioned that the lack of detailed information of the impact of LS of different study cases can lead to a bias in the evaluation of the index. That is, for some sites recorded in the database, the available information about land subsidence and its effects is very limited and this fact can introduce deviations in our calculations of the index. Another caveat of the LSIE is that a subsidence event could occur with only one type of impact, but severe, and would be seen as less important. For example, the case of Iran or Mexico, where subsidence occurs inland and flooding effects are unlikely, but the intensity of the other impacts is very harmful. In that respect LSIE does not provide a good quantification of the LS impact, but rather a measure of its extent. To address some of these caveats we introduced weights to the LSIE attributes, in an attempt to more appropriately reflect differences in the relative effects of these attributes.

3. Land Subsidence Extent and its Causes

LS occurs due to a combination of social, policy, and physical factors—stratigraphic, lithological and geomechanical characteristics of the aquifer system, and groundwater table depletion, or lowering of the piezometric head for a phreatic or confined aquifer system, respectively (Poland, 1984; Tomás et al., 2011; Gambolati and Teatini, 2015). This latter variable is controlled by the anthropogenic pressure on the aquifer system, usually represented by urban and agricultural demands, and is strictly related to the rate of groundwater pumping and policies to regulate water pumping (Poland et al., 1984; Freeze, 2000; Zhou et al., 2019). For the sake of completeness of reporting about the survey and analysis of literature LS impacts, definitions, impact evaluation, proxy variables, and results, we refer the readers to Appendix A Table A1.

We follow (See Appendix Table A1) the suggested list of causes identified in the various publications cited above, referring mainly to water availability, human pressure, aquifer lithology characteristics, governance and regulations (see also Kok and Costa 2021; Herrera et al. 2021). The general relationship that we estimate can be described by the following general equation:

$$LSIE = f(Scr, Pop, Irr, Suw, Lit, Dep, Reg, Dev) \quad [4]$$

where *Scr* indicates existence of water scarcity in the region that depends on the aquifer system. Scarcity leads to higher dependency on the aquifer system, making it more prone to LSIE. *Pop* is a measure for population growth rate in the region that depends on the aquifer system during the years over which the land has subsided, indicating the pressure for water supply on the aquifer system. Higher values of *Pop* mean a larger level of pressure on the aquifer system and thus, higher level of LSIE; *Irr* is a measure of whether or not irrigation occurs in the vicinity of the aquifer system that potentially can be overexploited and impact the LSIE; *Suw* measures availability of surface water in the region, suggesting a reciprocal impact of *Suw* on LSIE; *Lit* is a measure of the lithology of the aquifer system, indicating its stiffness. Aquifer systems that are loose will be more prone to LSIE; *Dep* is a measure of the groundwater level depletion during the years in which the aquifer system has subsided. A higher level of *Dep* is expected to lead to a higher value of LSIE; *Reg* is a measure of existence and effectiveness of groundwater pumping regulatory measures. A higher value of *Reg* is expected to lead to a lower level of LSIE. Finally, we introduce a variable (*Dev*) that indicates whether or not the aquifer system is located in a developing or a developed country, expecting that due to a more advanced governance in a developed country the associated LSIE level will be lower. An analysis of possible multicollinearity among these independent variables suggests that they are not correlated and, thus, multicollinearity is not a problem.

In summary, the model incorporates three types of causes: characteristics of the aquifer hydrogeological setting (*Lit*), regulatory intervention and governances (*Reg, Dev*), and pressure on the aquifer system (*Scr, Pop, Irr, Suw, Dep*). Each of these is expected to affect the extent of land subsidence in a different direction, as is analyzed below (See Appendix Table A1, column 1 and 4).

4. Study Area, Data, Variable Construction, and General Hypotheses

Technical published articles were retrieved, using search engines and publication databases, such as Jstore (www.jstor.org) and Agricola (https://www.ebsco.com/products/research-databases/agricola). We focused on technical papers in peer-reviewed journals and on books and book chapters. We searched only for English-written documents. We used the following keywords—land subsidence, groundwater, over-pumping, economic analysis, hydrology, land subsidence impacts—to search for titles, abstract contents, and keyword lists of the publications. The search team included one graduate student and two upper-level undergraduate students (serving as data analysts) overseen by the lead author of this paper over the period January 2019-June 2020.

A set of 183 papers was identified and read, separately, by the data analysts and were discussed for consistency and accuracy of the coding. Of the papers read, 45 were dismissed either because the information on land subsidence impact was not included, or because they focused on methods to model land subsidence. A total of 38 papers referred to same locations. For each location, information in the various papers related to that location was examined and consolidated. By the end of the data collection phase, we ended up with 119 different sites. Each site is characterized by a set of the variables, including coordinates of location of the aquifer system, to be used for collection of additional data that is geographically related. The variables that were collected or constructed are presented below with an explanation on how they were constructed. The 119 sites with identified LS span over 32 countries across the globe (Figure 1).

A recent publication (Herrera-Garcia et al. (2021)) identified 200 land subsidence locations around the world. Our search yielded 119 (119/200=59%) locations, but due to data deficiencies, we ended up with 113 (113/200=56%) locations in our operational dataset. Given the objective of devising the LSIE, the number of observations in our study is sufficient. Since we used published papers in peer reviewed journals we have considered their content as highly reliable.

LSIE was calculated as described in equation [3]. A given location facing LS effects could have between 1 and 10 types of LS impacts, thus, LSIE ranges between 0.1 and 1.0. The higher the LSIE value the more extreme is the LS effect in that site. LSIE is calculated using two assumptions: LSIE-EW assumes an equal weight for each of the ten attributes. We also developed a weighted version of LSIE (LSIE-W), employing a Delphi technique for obtaining a vector of weights assigned to each of the ten attributes. For a detailed description of the Delphi technique and the procedure we employed to obtain the weights of the ten attributes see Appendix B. LSIE-EW and LSIE-W are used as the dependent variable in the statistical analyses presented in the next section.

While the objectives of the various papers we surveyed and the methods they use differ, the information in the different papers surveyed by us provide also background information independent of the objective of the particular paper and the methods used. This allowed us to assign the binary (0/1) values to the different attributes we identified across the different studies. Because we measure the (existence of the) attributes as yes/no, we minimize the level of bias due to use of different measurement approaches and techniques. Indeed, this could be at the expense of assigning different groups of attributes the same score, even though, they might have different impacts.

4.*1 Impact of explanatory variables on LSIE*

The discussion below sets the direction of impacts of each of the explanatory variables on LSIE (directions of impacts are the same in the case of LSIE-EW and LSIE-W), ceteris paribus. Our hypotheses regarding the directions of impact between the explanatory variables and the LSIE are based on previous evidence found in the literature summarized in Appendix A (Table A1).

Scr, indicating water scarcity in the region that depends on the aquifer system, is a dichotomous variable (0/1) with a value of 1 if the region was mentioned as subject to drought, with no alternate water resources from groundwater or surface water (that can ease the pressure from the aquifer on site), or just a direct statement of water scarcity. A value of 0 would be assigned otherwise. Facing scarcity would imply a higher value of LSIE.

Pop, the population pressure on the water resources in the region, is measured by annual population growth and estimated as the slope of the linear regression equation of the three-year population observations of that location, spanning between 1995 and 2015 (or the nearest census years in the study area) as an indication for population growth trends. Note that this variable is drawn from either the jurisdiction where the study area is located at or nearest the provincial level jurisdiction if the area of study spans more than a single city. Positive values indicate an increase in population and negative values indicate population decrease. We assume that the effect of the *Pop* variable is quadratic. That is, as population grows, pressure on the aquifer water increases, but that effect is reduced due to population self-realization of water scarcity, and behavioral adjustment, after a certain level of consumption (Singh, 2018). Mathematically we expect $\frac{\partial LSIE}{\partial Pop} \geq 0; \frac{\partial^2 LSIE}{\partial Pop^2} \leq 0$.

Irr indicates whether irrigated lands are identified in or around the subsiding area, suggesting higher possible pressure on the aquifer system. This would imply that groundwater has been used for agricultural purposes. *Irr* is a binary variable (0/1) where 0 indicates that there is no evidence of groundwater use for irrigation, and 1 indicates otherwise. Having irrigated land in the region would imply a higher value of LSIE.

Suw indicates whether the area currently has access to alternative water sources (surface water such as lakes, rivers or reservoirs). It is a binary variable (0/1) where 0 indicates no evidences of alternative water source at surface level, and 1 otherwise. The determination of surface water availability was based on two methods: (1) whether existing research identifies the use of such water source in the area of study; and (2) if a major surface waterbody is located within the geographical boundary of the study area. Having access to alternative water sources would imply a lower level of LSIE.

Lit is a ranking variable associated with the lithology of the aquifer system, based on data in the global map by Hartmann and Moosdorf (2012). We ranked the identified lithologies of the aquifers based on their impact on land subsidence. Sediment-based lithologies are more prone to land subsidence than rock-based lithologies, and between sediments the unconsolidated ones are the most susceptible to face LS. Table 1 presents a classification of the main lithologies generally composing aquifer systems in relation to LS propensity. Class 1 encompasses unconsolidated sediments made by mixtures of sand, silt, and clays together with pyroclasts. Their stiffness is generally low and, consequently, Class 1 aquifer systems are very prone to subsidence. Class 2 includes the rocks "derived" from those sediments (e.g., mainly sandstones and conglomerates) with a lesser subsidence propensity. Aquifer systems belonging to Class 3 are all other kind of rocks with extremely low subsidence propensity. The lithology variable, *Lit*, captures what the LS literature suggests to be the lithological control of land subsidence (Notti et al., 2016). A higher lithology class —i.e. a stiffer soil—is associated with a lower level of LS.

<Table 1 About Here>

Table 1: Lithology class ranking for land subsidence propensity resulting from groundwater pumping.

Lithology class	LS Propensity Ranking
1. sedimentary unconsolidated	1
2. sedimentary siliciclastic	2
3. carbonates	3
4. sedimentary mixed	2
5. plutonic acid	3
6. volcanic acid	3
7. metamorphic	3
8. pyroclasts	1
9. volcanic intermediate	3

Source: Authors elaboration based on map in Hartmann and Moosdorf (2012).

Note: Propensity to LS declines as values increase from 1 to 3.

Dep represents the groundwater depletion during a given period (loss in water table levels) and is based on data generated by the WaterGAP model (Döll et al., 2014). The generated data provide year-to-year change of groundwater levels between 1960 and 2010 for each aquifer system in our dataset. Negative values represent depletion and positive ones are rise of groundwater levels. Based on this dataset, we created two depletion variables: (1) Dep_1 = GW_*Depletion_1960-2010* which is the net depletion during 1960-2010, measured as the difference between the GW level in 2010 and in 1960; (2) Dep_2 = *Trend_GW_Depletion* which is the slope of the regression line going through the set of five decadal GW depletion data points.[1] Decadal GW Depletion 2000-2010, for example, is the loss in GW level between 2000 and 2010. It is assumed that Dep_1 or Dep_2 are affecting LSIE such that the larger is Dep_j , j=1, 2, the larger is the effect on LSIE, and that this effect increases at an increasing rate as Dep_j , j=1, 2, grows beyond a given level (because higher values of Dep_j j=1, 2, introduce new dimensions/attributes of LSIE). Mathematically we expect that $\frac{\partial LSIE}{\partial Dep_j} > 0$, and $\frac{\partial^2 LSIE}{\partial {Dep_j}^2} > 0$ for j=1,2.

Reg is an ordinal (ranking) variable measuring whether each site has established adequate control measures on groundwater extraction. A value of 1 indicates that the site has no legislations or regulations to controll groundwater use and has no enforcement efforts in place. A value of 2 was assigned if some regulatory efforts are in place but are not enforced or have suffered through prolonged mismanagement of its groundwater resources. A value of 3 was assigned to the site if evidence suggests a history of regulatory efforts are in place and such regulations have been adequately managed. The more effective the regulations and enforcement, the lower is LSIE.

Dev indicates whether the country in which the aquifer with LS impact is a developing country (=1) or a developed country (=0). Developed countries with improved level of governance may face lesser problems of water mismanagement (Saleth and Dinar, 2004), and thus, a developed country is expected to face a lower level of LSIE.

We also introduced two interaction terms in our model. The interaction variable *Irr* x *Suw* allows to determine whether or not the effect of nearby irrigated land in the site depends on whether the site has access to alternative water sources. In the same way we introduced the interaction variable *Reg* x *Dev* to determine whether or not a site with higher level of regulation of GW extraction depends on whether or not the country to which it belongs is a developed or a developing country.

[1] Decadal GW Depletion 2000-2010, Decadal GW Depletion 1990-2000, Decadal GW Depletion 1980-1990, Decadal GW Depletion 1970-1980, and Decadal GW Depletion 1960-1970.

5. Empirical Specifications and Hypotheses

The model in [4] is developed using linear terms for all variables and quadratic relationships for *Pop* and *Dep*. Given that our dependent variable, LSIE, contains real values that range from 0.1 to 1.0 and between 0.028 and 0.960 for LSIE-EW and LSIE-W, respectively, we use the ordinary least squares (OLS) estimation procedure to uniquely identify the model. Since our dependent variable is continuous it is justified to employ a linear equation with quadratic terms for the continuous independent variables. By estimating a linear relationship between LSIE and the explanatory variables we allow a simple procedure to calculate their marginal effect on LSIE. In addition, because several of the dependent variables are dichotomous, we can include them in the estimated relationship only as dummies.

The variables $Scr,\ Irr,\ Suw,\ Dev$ are dichotomous variables and are introduced in the estimated equation as dummies that affect the level of the intercept (constant) of the estimated equation. *Reg* and *Lit* are introduced as linear ranking variables. *Pop* and *Dep* are introduced in linear and quadratic forms, due to the expectation that their marginal impact on LSIE would be marginally diminishing or increasing, respectively.

The general expression in [4] was transformed into explicit functions with linear terms for the non-continuous variables (*Scr*, *Irr*, *Suw*, *Lit*, *Reg*, *Dev*), and linear and quadratic terms for the continuous variables (*Pop*, Dep_j, j=1, 2) as can be seen in equation [5], and two interactive terms *Irr*×*Suw* and *Dev*×*Reg*. Just to reiterate, it has to be considered that a quadratic variable with linear and quadratic terms indicates that the effect of that variable (whether positive or negative) on the dependent variable could be either marginally diminishing (if the coefficient of the quadratic term is negative) or marginally increasing (if the coefficient of the quadratic term is positive).

The general empirical version of the estimated relationship is as follows:[2]

$$LSEI_j^k = \alpha_j^k + \beta_j^k \cdot Scr + \gamma_j^k \cdot\ Pop + \delta_j^k \cdot Pop^2 + \varepsilon_j^k \cdot\ Irr + \theta_j \cdot Suw +\ \vartheta_j^k \cdot Lit + \lambda_j^k \cdot Dep_j + \xi_j^k \cdot {Dep_j}^2 + \mu_j^k \cdot Reg + \phi_j^k \cdot irr \times Suw + \zeta_j^k \cdot Reg \times Dev + u^k. \qquad [5]$$

where $\boxdot_j^k$ is any of the estimated coefficients $\alpha, \beta, \dots, \phi, \zeta$, j=1, 2 stands for the two versions of groundwater depletion variables that were defined earlier, and *k* stands for any possible version of

[2] The estimated coefficients of Equation [5] are used to infer our hypotheses, as they were spelled out in section 4.

this equation, such as a version that is solely linear (excluding the quadratic terms of Pop^2 and $Dep_j^{\ 2}$(j=1, 2), or a version that does not include certain explanatory variables). u^k is the error term. We employed the software Stata 13 to estimate the various model equations.

To keep the values of the independent variables within similar scales, we transformed *Pop* from persons to thousands of persons $PopK=Pop/1000$ and Dep_2 from mm (as is in the original dataset) to meters: $Dep_2K=Dep_2/1000$.

The weights of the ten attributes that we obtained from the Delphi technique are presented in section 6.1.

6. Results

The analysis in this paper utilizes only 113 of the 119 observations, due to missing values of depletion of groundwater in aquifers in some of the sites and due to one outlier observation (The Mekong Delta). One possible explanation for being an outlier is that the observation in the Mekong Delta (serving 10.7 million people) spans over a very wide region with many different geological, hydrological, and social/economic conditions that could lead to unexpected behavior of LS effects. Therefore, we decided to remove that observation from our dataset and continue with 113 observations for the statistical analysis.

6.1 Land Subsidence Sites and their Attributes

A map with all sites that were identified in our literature review and included in the dataset with LS impacts is presented in Figure 1.

<Figure 1 About Here>

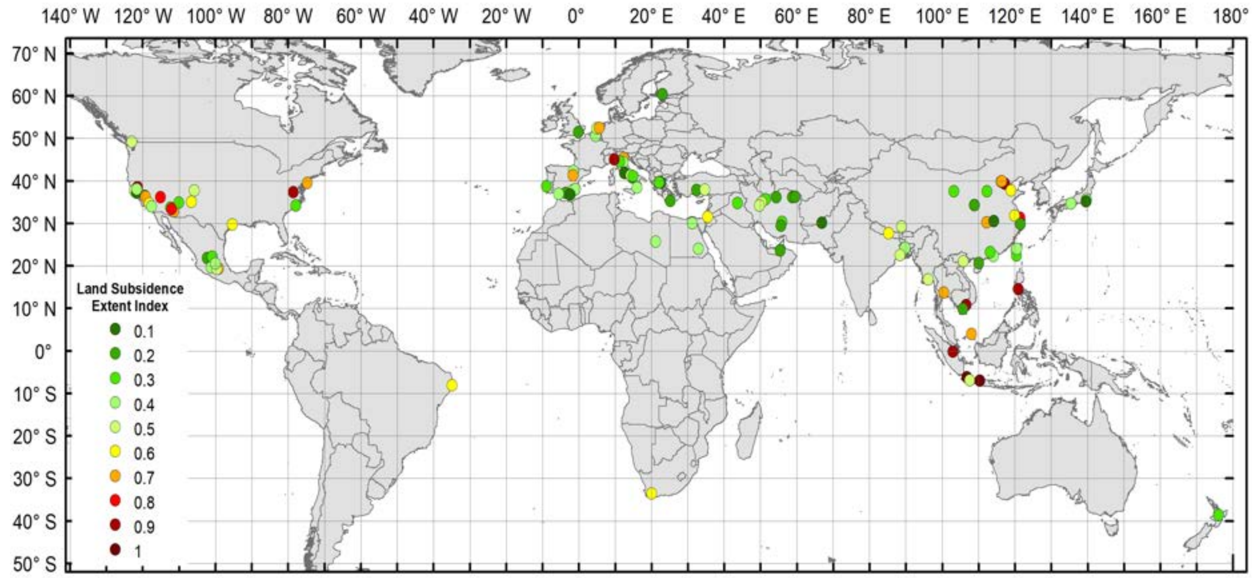

Figure 1: Global impact extent of land subsidence in sites in the dataset.

Source: Authors' elaboration.

NOTE for production (if accepted): This figure should be produced in color.

A distribution of the 10 land subsidence attributes that comprise the LSIE, based on what has been reported for the various locations in our dataset, is presented in Table 2. The values in the column "Mean" should be interpreted as the frequency of each of the LSIE attributes in the regions with LS impacts. Remember that attributes are non-mutually exclusive, so that some locations may experience one attribute, some may experience 10 attributes, and some may experience anywhere between 1 and 10 attributes. Because all locations in our dataset face LS effects, there is no location reporting 0 attributes.

<Table 2 About Here>

Table 2: Distribution of land subsidence attributes across the sites in the dataset.

LSIE Impact Attributes	Mean	SD	CV (%)
1. Socio-economic impacts, such as structural damages	0.771	0.422	54.7
2. Environmental damages, such as malfunctioning of drainage systems	0.593	0.493	83.1
3. Geological-related damage altering subsurface lateral water flow direction	0.568	0.497	87.5

4. Environmental damages, such as reduced performance of hydrological systems	0.568	0.497	87.5
5. Environmental damages, such as wider expansion of flooded areas	0.559	0.499	89.2
6. Hydrogeological damages that result in groundwater storage loss	0.551	0.500	90.7
7. Impact on adaptation ability to climate change	0.297	0.459	154.5
8. Groundwater contamination	0.229	0.422	184.2
9. Loss of high-value transitional areas (e.g., saltmarshes)	0.127	0.335	263.8
10. Shift of land use to poorer activities	0.110	0.314	285.4

Note: A more detailed description of each impact attribute can be found in the introduction section.

The results in Table 2 suggest that the most common impact attribute that was identified in the literature we reviewed reported in 77% of the cases as socioeconomic impacts of LS, while the least common impact attribute, reported in 11% of the cases, is shift of land use to poorer activities. Impact attributes 1-6 show frequency of 55-77%, while impact attributes 7-10 are relatively rare (11-30%). An interesting result in Table 2 is that impact attributes with higher occurrence levels are also characterized with a lower coefficient of variation (CV), indicating a lower degree of variability. For example, the socioeconomic impacts of LS (mean of 0.771) are characterized with a CV of 54.7, while shifts of land use to poorer activities (mean of 0.110) are characterized with a much higher CV equal to 285.4. Yet, these CV values are considered relatively small and, thus, the mean is representative of the sample.

The weights of the ten attributes resulting from the Delphi technique are presented in Table 3.

<Table 3 About Here>

Table 3: LSIE-W weights (percent) of the ten attributes as obtained from the Delphi technique (sum=100)

LS Attribute									
1	2	3	4	5	6	7	8	9	10
Weights (Percent)									
18.111	10.778	2.778	6.667	22.777	12.556	9.556	7.667	5.222	3.888

6.2 Descriptive Statistics

Table 3 presents the descriptive statistics of the change in groundwater level change (m) over the 50 years from 1960 to 2010. A few aquifer systems show an increase in water table level, while most show depletion. Mean depletion over the 50 years was 12.11 m. The decadal results are interesting by themselves because it is very clear that the mean decline increases from 0.89 meter per decade in 1960-1970, to 3.61 m per decade in 2000-2010. In addition, the standard deviation of depletion increases as well over the five decades from 2.23 m to 9.21 m. Both trends suggest that the long-term effects of pumping groundwater will most likely result in a higher likelihood of land subsidence, as reflected in the LSIE.

<Table 3 About Here>

Table 3: Descriptive statistics of decadal groundwater level change (m per decade) between 1960-2010 in the various aquifer systems of the dataset.

Decade	1960_2010	1960_1970	1970_1980	1980_1990	1990_2000	2000_2010
Mean	-12.11	-0.89	-1.81	-2.65	-2.91	-3.61
SD	32.14	2.23	5.86	7.65	7.96	9.21
Min	-239.38	-14.92	-51.43	-66.04	-61.18	-54.66
Max	0.59	0.33	0.48	0.51	1.46	0.75

Note: Negative values (Mean and Min) indicate a decline, positive values (Max) indicate an increase.

The mean decline of groundwater level is more than 12 meters during 1960-2010. Decadal variation of groundwater depletion level ranges between a decline of 66 meters, and a 1.5-meter increase.

<Table 4 About Here>

Table 4: Descriptive statistics of variables considered for the regression analysis.

Variable	Description (units)	Mean	Standard Deviation	Minimum	Maximum
LSIE-EW	Land Subsidence	0.444	0.227	0.1	1

	Extent Index with equal weights (Real number between 0.1-1.0)				
LSIE-W	Land Subsidence Extent Index with weights (Real number between 0.028-0.960)	0.508	0.247	0.028	0.960
SCR	Water scarcity (Dichotomous)	0.964	0.186	0	1
PopK	Population change (1000 people per year)	92.856	212.353	-3.529	1384.200
Irr	Irrigation water use (Dichotomous)	0.619	0.487	0	1
Suw	Available surface water (Dichotomous)	0.451	0.499	0	1
Reg	Effective GW regulations (Ranking)	1.761	0.735	1	3
Lit	Lithology (Ranking)	1.460	0.762	1	3
Dep_1K	GW depletion 1960-2010 (meters)	12.11	0.301	-0.041	239.38
Dep_2	GW periodical depletion (meters/decade)	-6.470	-17.776	-112.430	13.922
Dev	Developing Country (Dichotomous)	0.487	0.502	0	1

Note: For the continuous variables negative values indicate decrease and positive values indicate increase.

Number of observations is 113.

Results in Table 4 indicate that, LSIE-EW mean level in our dataset is 0.444, which suggests 4-5 attributes per location. LSIE-W mean level in the dataset is 0.508, suggesting 5 attributes per location. A total of 96% of the locations in the analysis face water scarcity, which makes this variable irrelevant for the statistical analysis due to lack of variance; 62% of the regions have irrigation projects that also utilize a groundwater source; only 42% of the regions have access to surface water; the mean lithology is between Class 1 and Class 2, suggesting that aquifer systems in our dataset are prone to LS. The mean regulation ranking is 1.761, which suggests that, on average, regulation of groundwater pumping occurs but it is not effective. Finally, nearly 50% of the regions experiencing LS in our sample are in developing countries.

6.3 Estimation Results

We estimated models of LSIE causes. We used two versions of LSIE as the dependent variable: LSIE-EW and LSIE-W. The variable Dep_1K was not significant in any of the estimations and is not included in the results. Models 2 and 4, include the regulatory variable *Reg*, while models 1 and 3 do not include tis variable. Furthermore, all models include also the interaction terms of *Irr*×*Suw* and *Dev*×*Reg*. Estimation results are presented in Table 5.

<Table 5 About Here>

Table 5: Results of the LSIE equation estimates.

Model	1	2	3	4
	LSIE-EW	LSIE-EW	LSIE-W	LSIE-W
Intercept	0.565 (9.29)***	0.620 (7.91)***	0.651 (9.75)***	0.673 (7.77)***
PopK	1.057E-03 (3.49)***	1.014E-03 (3.32)***	9.869E-04 (2.96)***	9.699-04 (2.88)***
PopKsq	-8.082E-07 (-3.03)***	-7.667E-07 (-2.85)***	-7.872E-07 (-2.69)***	-7.709E-07 (-2.60)***
Reg	-	-0.031 (-1.12)	-	-0.012 (-0.40)
Suw	-0.176 (-2.57)***	-0.183 (2.65)***	-0.142 (-1.88)**	-0.144 (-1.90)**
Lit	-0.053 (-1.79)**	-0.053 (-1.81)**	-0.0590 (-1.84)**	-0.059 (-1.85)**

Dep_2	6.040E-03 (2.00)**	5.962E-03 (1.98)**	7.134E-03 (2.15)**	7.10E-03 (2.14)**
Dep_2sq	5.99E-5 (1.96)**	6.043E-05 (1.98)**	7.759E-05 (2.31)**	7.777E-05 (2.30)**
Irr×Suw	0.106 (1.46)*	0.115 (1.57)*	0.051 (0.65)	0.055 (0.68)
Dev×Reg	-0.051 (-1.91)**	-0.049 (1.84)**	-0.055 (-1.90)**	-0.055 (-1.86)**
Observations	113	113	113	113
Adjusted R-Square	0.114	0.116	0.091	0.084
F-test	2.804***	2.640***	2.410***	2.143**

Note: in parentheses are t-statistic. *, **, and *** indicate significance at 10, 5, and 1%, respectively.

In general, the results of the various estimated models (Table 5) support our different a-priori hypotheses. All estimated coefficients have the expected sign, they show robustness across the models, they are significant at 1 to 10%. Adjusted R-square values of the 4 estimated equations range between 8 and 12%, which is reasonable for a dataset that includes variables that were collected from various sources. The F-tests are significant at the 1% level for models 1 to 3 and at the 5% level for Equation 4. The fact the models with the two dependent variables—LSEI-W and LSEI-EW—resulted in very, statistically, similar sets of coefficients indicates a high level of robustness of our analytical framework.

For all models the population variable indicates a quadratic effect with *PopK* being positive and *PopKsq* being negative, which indicates a quadratic effect on LS. Because *PopKsq* is very small, the quadratic effects on LSIE are monotonic. But, in general for all models, the larger the annual population growth trend the greater is the extent of LS, and this effect is incrementally declining with the increase in population growth.

The variable *Reg*, measuring effectiveness of regulatory policies, has a negative coefficient suggesting that as regulations become more effective, LSIE is reduced. However, the estimated coefficients of this variable are not significant. Suspecting that level of effectiveness of groundwater regulatory policies is also affected by the overall level of water governance in the country, we introduced the interaction variable *Dev×Reg,* which measures the effect of overall governance and the specific effect of groundwater management regulatory policies. The coefficient of the interaction term is negative and significant in all models, suggesting that in developing countries and in regions with effective policies, the level of LSIE is lower.

The variable *Suw*, which indicates whether or not there is a source of surface water to satisfy the needs of the region, in addition to groundwater, has a negative and significant coefficient. This means that having an additional surface water source releases the pressure on aquifers, which translates into a lower LSIE. However, an interaction term *Irr*×*Suw* was also introduced to capture the possible effect of utilization of the surface water source for irrigation and creating pressure on the region. Estimated coefficients in Table 5 suggest that this interaction term has a positive sign, suggesting that both irrigation site and a source for surface water used for irrigation will increase the level of LSIE, suggesting that having the additional source of surface water used for irrigation introduces additional pressure on the water resources in the site. This interaction term is significant at 10% level in models 1 and 2 (LSIE-EW).

The *Lit* variable, characterizing the lithology type of aquifer systems suggests that higher levels of the lithology ranking (Table 1), which means a stiffer aquifer system, is associated with lower LSIE. The estimated coefficients of the *Lit* variable are significant at 5% in all models).

Finally, the decline of groundwater level is modeled as a quadratic relationship. We use the variable Dep_2. In all models both the linear component (Dep_2) and the quadratic component (Dep_2sq) are positive and significant, which means that the effect of groundwater level depletion on land subsidence extent increases in an increased rate.

7. Policy Simulations

Several of the variables in the investigated models provided in Table 5 could be considered for policy intervention options using the sign and value of the regressors to quantify their incremental effects. To keep the paper length, we will demonstrate the effects of policy impacts using model 1 only. The analysis includes the effects of population change (*Pop*), access to surface water (*Suw*), reduction in GW level (*Dep*), and indirectly the interactions between governance level and regulation effectiveness (*Dev*×*Reg*) and between access to surface water and irrigation (*Sue*×*Irr*).

We conduct two simulations: First we analyze marginal effects, using mean values of the relevant variables, and then we conduct a ‘with and without’ analysis of those variables.

7.1 Marginal effect of policy interventions

Each of the marginal effects below is analyzed, assuming all other remain unchanged. The marginal effect of population change, which represents pressure on the aquifer system, is determined by $\frac{\partial LSEI}{\partial Pop} = 0.001057 - 2 \cdot 8.082 \cdot 10^{-7} \cdot \overline{PopK}$, where $\overline{PopK}$ is the sample mean (=92.856). The calculation of the incremental effect of population change at the sample mean yields $\frac{\partial LSEI}{\partial Pop}$ =0.0009085. This means that the incremental effect of population growth, will result in an increase of nearly 0.0009 units of the land subsidence extent or less than 0.1%.

The marginal effect of access to surface water source is measured as $0.1058 \cdot \overline{Irr}$, where $\overline{Irr}$ is the sample mean (=0.619) of having the irrigation sector use of such water. The calculation yields a marginal effect that equals 0.065. This means that having access to a surface water source used for irrigation, in addition to the aquifer water will result in an increase in the land subsidence impact extent of nearly 0.065 units, or 6.5%.

The marginal effect of groundwater level depletion is measured by $\frac{\partial LSEI}{\partial Dep_2} = 0.00604 + 2 \cdot 5.997 \cdot 10^{-5} \cdot \overline{Dep_2}$, where $\overline{Dep_2}$ is the sample mean (=-6.470). The calculation of the incremental effect of groundwater level depletion at the sample mean yields $\frac{\partial LSEI}{\partial Dep_2} = 0.00526$. This means that the incremental effect of the groundwater level depletion will result in an increase of nearly 0.0053 units of the land subsidence extent, or nearly 0.5%.

The marginal effect of the variable that measures interaction between regulation effectiveness and level of governance is $-0.051 \cdot \overline{Dev}$, where $\overline{Dev}$ is the sample mean (=0.487). This means that the increase in groundwater regulations and governance, in general, will result in a reduction of the land subsidence extent of nearly 0.025 LSIE units. Due to the measurement of LSIE, this means a reduction of nearly 2.5%.

To sum up, the marginal effects of regulation (*Reg*), population (*PopK*), groundwater level depletion (Dep_2), and of access to surface water source (*Suw*) on the LSIE-W are -0.025, +0.0009085, +0.0053, and $+0.065$, respectively, with a total sum of the marginal effects of -0.013, or nearly 1.5%. This also means that the variables included in our estimation have opposite effects on land subsidence and, thus, policy interventions with opposed effects should be carefully considered. In addition, the variable with the most measurable effect (of nearly 10%) is the existence of a source of surface water supply, which for our purposes could also be any other source of manufactured water. This result provides a direction for prioritizing policies for addressing land subsidence. This set of considerations will be discussed in the next section.

7.2 With and without effects

Under the with and without analysis we use the mean value for the continues variables (*Pop*, and *Dep*) and for the ranking variables (*Lit*, and *Reg*) while we switch between 1 and 0 to account for ‘with’ and ‘without’, respectively for *Dev*, *Irr* and *Suw*. Results are presented in Table 6.

Table 6: Impact of dichotomous variables on level of LSIE-EW using ‘with and without’ effects.

Senario	1 SUW=1 IRR=1 DEV=1	2 SUW=0 IRR=0 DEV=0	3 SUW=1 IRR=0 DEV=1	4 SUW=1 IRR=1 DEV=0	5 SUW=0 IRR=1 DEV=1	6 SUW=0 IRR=1 DEV=0	7 SUW=0 IRR=0 DEV=1	8 SUW=1 IRR=0 DEV=0
LSIE-EW	0.3829	0.3667	0.2769	0.4727	0.4529	0.5427	0.4529	0.4708

Notes:

(1) Equation used: LSIE-EW=0.565+0.001057*POP-0.000000808*POP*POP-0.176*SUW-0.053*LIT+0.00596*DEP+0.0000604*DEP*DEP+0.106*IRR*SUW-0.051*DEV*REG

(2) Mean values used for continuous variables: POP=92.856; LIT=1.46; DEP=-6.47; REG=1.761.

Results in Table 6 shows that the level of LSIE-EW is sensitive to the combination of the dichotomous variable that indicated access to surface water sources, competition between the urban and the irrigated sector, and whether or not the country under which land subsidence occurs is a developed or developing one.

Indeed, it appears that for all combinations of the 3 control variables, the impact of having an irrigation project resulted in a higher level of LSEI-EW, suggesting higher stress on the groundwater resources when irrigation is present. In the same way it is evident that the level of land subsidence impact is higher when access to surface water resources are not available and the locality relies only on the aquifer water.

8. Discussion, Policy Implications, and Limitations

In spite of its major social cost in hundreds of locations around the world, the majority of which have irreversible negative physical and economic impacts, land subsidence has not been given proper preventive attention by regulatory agencies and local water management organizations in many countries. We were able to identify and analyze land subsidence effects in 113 locations where mainly physical consequences of land subsidence have been assessed but economic damages, likely in the range of billions of dollars, have not been quantified. In the absence of a method for estimating economic value for the LS-induced damage, we developed a land subsidence extent index (LSIE) that relies on the occurrence of up to 10 land subsidence effects that were observed in these sites. This assessment allows the identification of different types of impacts in different locations and is used to explain the effects of physical conditions, such as aquifer lithology, managing institutions, social systems, existing policies, population pressure, water-level depletion from over pumping, and several other variables on LSIE. While this approach may lead to a comparative assessment of the impact of land subsidence across sites, we are aware of its limitations as a measure for land subsidence for comparing damages and impacts across sites.

The results of our analysis indicate the importance of effective policy regulations on reducing impact of land subsidence, captured in lower values of LSIE. Our results suggest also that developing countries are more prone to higher levels of LSIE, mainly because of mal-performing institutions and lesser success of the governance system. This suggests that improving groundwater management in developing countries may be more beneficial once the negative impacts of land subsidence are considered. In addition, a general conclusion from this analysis is that more resources and efforts should be allocated by international agencies to the systematic and comparative analysis of drivers of land subsidence and measurements of land subsidence economic impacts.

The results obtained in this study may provide useful insights for policy implications such as that policies for groundwater regulation could be less effective for land subsidence in developing countries than in developed countries. This suggests that a more rigorous regulatory intervention approach should be considered for countries with malfunctioning institutions and lower levels of governance. We also can derive several lessons regarding the need to establish policies that consider development of various water resources and their conjunctive use in order to ease pressure on the aquifer systems in regions under risk of land subsidence. This includes importing surface water, developing or investing in technologies (desalination of brackish or seawater, treating wastewater) to amend water supply to the regions, policies for curbing groundwater extractions, developing programs to introduce incentives for recharge of various types of water into the aquifer in years of supply abundance, and instituting the framework to allow water trade within and between regions that face risk of land subsidence.

Several limitations of our study should be mentioned. First, in an absence of exact number of the population relying on the aquifer system and the size of the aquifer system in question, we can introduce a bias to the LSIE calculation. Second, we have used for the calculation of population growth rate an acceptable range of years (1995-2015) within which the land subsidence reported in the regions in our sample have taken place. However, it could well be that significant increase in the population in these regions started much earlier and triggered the impacts on the aquifer systems. Therefore, results regarding population growth have to be cautiously viewed.

One important aspect that we were not able to accomplish in our work is to compare out results with those obtained in previous similar studies. This is unfortunately impossible to obtain mainly due to the innovative nature of our approach in developing a global index for land subsidence extent. All known studies that estimate physical impact or even economic impact of land subsidence are limited to one region, or several regions within one country, and thus cannot be compared with global findings. One study that could be considered the closest to our work in terms of global assessment of land subsidence impacts, the Herrera-Garcia et al. (2021), evaluates the impacts in terms of general, state-level, welfare losses, while we look at LS site-specific effects.

Our plan of research for the coming years is to develop a framework to estimate the total effects of land subsidence and to apply it to a series of studies in different parts of the world. This will allow building a set of comparable case studies that will facilitate the aggregation of economic effects of land subsidence in various parts of the world.

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Appendix A: Table A1. Summary of the survey and analysis of literature LS impacts, definitions, impact evaluation, proxy variables, and results.

LS attributes	References	Impact evaluation	Proxi variables in LSIE [0.1,1.0]	Results
3. Geological-related damages: Effects on underground lateral water flows	[3]	Aquifer lithology and hydrogeology Physical factors	Lit [1/2/3]	↗Lit ↗LSIE
6. Hydrogeological damages resulting in groundwater storage loss	[4]			
5. Environmental damages: Such as wider expansion of flooded areas	[3]	Water level Depletion Physical factors	Scr [0/1]	Not included due to non-variability
			Pop (numerical)	↗Pop ↗LSIE Pop ∩
4. Environmental damages: Such as reduced performance of hydrological systems	[3]		Irr [0/1]	Non-significant ↗Irr ↘LSIE
8. Groundwater contamination such as seawater intrusion resulting in decrease of farmland productivity	[3], [4]		Suw [0/1]	↗Suw ↘LSIE ↗Irr x Suw ↗LSIE
2. Environmental damages: malfunctioning of drainage systems	[2]		Dep (numerical)	↗Dep ↗LSIE Dep ∪
7. Impact on adaptation ability to climate change	[5]			
9. Loss of high-value areas	[2]			
10. Shift of land	[6]			
1. Socio-economic	[1]	Managing institutions and existing policies Social and policy factors	Reg [1/2/3]) Reg x Dev Dev [0/1]	Non-significant ↗Reg x Dev ↘LSIE ↗Reg ↘LSIE

Notes: Attributes in Table A1 are not in order due to need to fit the impact evaluation criteria.

References: [1] = Bru et al. (2013); [2] = Viets et al. (1979); [3] = Poland (1984); [4] = Holzer and Galloway (2005); [5] = Erkens et al. (2016); [6]= Heri et al. (2018).

Appendix B: Assigning weights to the LSIE attributes using the Delphi technique

Deciding on parameters to be used in analyses is always a challenge, especially when the knowledge base is narrow, or without measurable information. Regulators, politicians, managers, and public officials have been benefiting from the application of the Delphi technique – a widely used instrument to aggregate individual expert judgments into refined opinion, either to forecast future events, or to estimate current status, intentions, or parameter values. A detailed description of and discussion about the Delphi Technique can be found in various publications such as, Linstone and Turoff, (1975a, b) and Webler et al., (1991)).

The Delphi technique relies on a structured, yet indirect, approach to quickly and efficiently elicit responses relating to group learning and forecasting from experts who bring knowledge, authority, and insight to the problem, while, at the same time, promoting learning among panel members. It records facts and opinions of the panelists, while avoiding the pitfalls of face-to-face interaction, such as group conflict and individual dominance.

Several limitations have also been recognized in the application of the Delphi technique. Besides possible poor design, and execution of the process, which might affect the application of any other technique, the Delphi technique is sensitive to selection of panelists that can deliberately promote desired outcomes or influence future decisions – making the selection of panelists very important. Another disadvantage of the Delphi technique is that there is no way to assign higher or lower reliability scores to technical panelists compared with lay panelists.

The Delphi process exists on 'iterative' and 'almost simultaneous' forms. While the first form consists of a monitoring team that regulates and coordinates the process, the latter one is mechanized (computer, web), and allows real-time responses and updates. However, the Delphi process, in either form, consists of four basic phases: (a) exploration of the subject under consideration, (b) understanding how each panelist views the issue, (c) in case of disagreement, understanding the reasons for such differences, and (d) feedback, final evaluation and consensus.

We applied the Delphi process to estimating weights of the 10 land subsidence attributes that comprise the LSIE. We selected a team of 9 experts on land subsidence [from the Netherlands, China, Pakistan, Spain, Italy, California (USA), Louisiana (USA), and Virginia (USA)].

The experts were provided with a table that describes the components of the LSIE and were asked to assign weights (in %) to each (summing to 100). We used the same definitions as in the manuscript:

1. Socio-economic impacts: Damage to infrastructure
2. Environmental damages: malfunctioning of drainage systems
3. Geological-related damages: Effects on underground lateral water flows
4. Environmental damages: Such as reduced performance of hydrological systems
5. Environmental damages: Such as wider expansion of flooded areas
6. Hydrogeological damages: Resulting in groundwater storage loss
7. Impact on adaptation ability to climate change: Such as the loss of the buffer value of groundwater in years of scarcity
8. Groundwater contamination: Such as seawater intrusion resulting in decrease of farmland productivity in coastal aquifer systems and decrease of fresh-water availability
9. Loss of high-value transitional areas: Such as saltmarshes
10. Shift of land use to poorer activities: Such as from urbanized zones to rice fields, from rice fields to fish and shellfish farms, from fish farms to wastewater ponds

At the onset of the Delphi process, the 9 experts were given the basic information on the 10 attributes and their definitions. The experts were asked to assign weights to each attribute. Two co-authors of the paper administered the process and collected and analyzed the feedback from the panel experts. The process would be terminated when there is no attribute with a coefficient of variation across the experts or the mean across the 10 attributes which exceeds 50-60% (Woudenberg, 1991). The process terminated after two rounds. The data and analysis of the feedback from the experts per round are presented below.

Table B1: Data from round 1 of the Delphi technique

Expert	LSIE Attribute									
	1	2	3	4	5	6	7	8	9	10
	Percent									
1	25	25	2	2	30	4	2	4	5	1
2	15	8	1	5	25	30	5	5	5	1
3	20	15	5	5	25	5	5	5	10	5
4	20	15	2	5	25	5	10	10	5	3
5	30	8	5	5	30	7	6	5	2	2

6	10	3	1	10	20	5	30	10	6	5
7	15	10	5	10	5	15	15	15	5	5
8	15	5	10	10	15	20	0	10	5	10
9	20	10	5	5	25	15	5	5	5	5

Table B2: Descriptive statistics of the results for the LSIE attributes in Round 1 (9 experts)

	LSIE Attribute									
	1	2	3	4	5	6	7	8	9	10
CV	31.814	59.959	71.807	46.034	35.773	76.034	105.120	48.804	38.654	68.200
Mean	18.889	11.000	4.000	6.333	22.222	11.778	8.667	7.667	5.333	4.111
Standard Deviation	6.009	6.595	2.872	2.915	7.949	8.955	9.110	3.742	2.062	2.804
Standard Error	2.003	2.198	0.957	0.972	2.650	2.985	3.037	1.247	0.687	0.935
Minimum	10	3	1	2	5	4	0	4	2	1
Maximum	30	25	10	10	30	30	30	15	10	10

As can be seen from Table B2 the first round of elicitation of land subsidence attribute weights yielded coefficients of variations values in access of 50% for 5 of the 10 attributes. In addition, the overall variation across all 10 attributes, measured via the coefficient of variation of all attributes and panel experts was 59.25%

As a result, we shared the mean weight values for the 10 attributes with the group of experts and requested that they consider modifying their weight assessment of all 10 attributes. The results of the second round of assessment is presented in Table B3.

Table B3: Data from round 1 of the Delphi technique

Expert	LSIE Attribute									
	1	2	3	4	5	6	7	8	9	10
	Percent									
1	23	20	2	5	25	8	5	5	5	2
2	15	8	1	5	25	30	5	5	5	1
3	20	14	4	5	25	7	6	6	8	5
4	20	12	2	5	25	8	10	10	5	3

5	20	10	5	5	25	10	10	8	3	4
6	10	3	1	10	20	5	30	10	6	5
7	20	10	5	10	15	10	10	10	5	5
8	15	10	0	10	20	20	5	10	5	5
9	20	10	5	5	25	15	5	5	5	5

We repeated our calculation of the coefficient of variation for all 10 LSIE attributes in Round 2. The descriptive statistics of the 10 attributes is presented in Table B4.

Table B4: Descriptive statistics of the results for the LSIE attributes in Round 2 (9 experts)

	LSIE Attribute									
	1	2	3	4	5	6	7	8	9	10
CV	21.990	42.462	71.498	37.500	15.947	63.481	83.902	31.277	24.926	39.512
Mean	18.111	10.778	2.778	6.667	22.778	12.556	9.556	7.667	5.222	3.889
Standard Deviation	3.983	4.577	1.986	2.500	3.632	7.970	8.017	2.398	1.302	1.537
Standard Error	1.328	1.526	0.662	0.833	1.211	2.657	2.672	0.799	0.434	0.512
Minimum	10	3	0	5	15	5	5	5	3	1
Maximum	23	20	5	10	25	30	30	10	8	5

As can be seen from Table B4, the values of the coefficients of variation have declined for all attributes in Round 2 compared to Round 1. The mean CV across all 10 attributes declined from 59.25% in round 1 to 43.24% in round 2. These two results led us to truncate the process of getting feedback from the 9 LS experts. The mean weights for each attribute in Table B4 were used for the calculation of the weighted LSIE in our regression analysis (rounding values beyond the decimal point to obtain a total value of 100 for the LSIE).

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