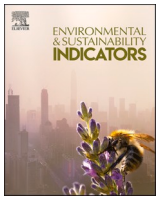
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A tool for the estimation of the magnitudes and monetary values of ESS losses and returns on investment to combat degradation of agricultural resources☆

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ABSTRACT

Reversing the effects of agricultural resource degradation – and its implications for ecosystem services (ESS) – require targeted policy action. Comprehensive and consistent estimates of the magnitudes and monetary values of the loss of ESS due to inaction and avoided losses due to action to prevent and reverse agricultural resource degradation (ARD) can provide strong evidence that motivate investment and unlock financing mechanisms. In this paper, we present a decision support tool called "Analysis Pack for Economics of Agricultural Resource Degradation and Ecosystem Service Losses (APEARD)" which we developed not only to provide estimates of losses for different ESS, but also to evaluate the returns on investment and sustainability of co-benefits of actions. A national-scale application of APEARD, presented here only as proof of its versatility, shows that inaction on ARD is costing Uzbekistan potential production of at least 2 million tons of food, 63.8 thousand tons of woody biomass, and 477 thousand tons of forage, and 18.2 billion cubic meters of irrigation water, and 194 million tons of soil annually. ARD is also causing the emission of 1.6 million tons of carbon annually, among other hazards. These impacts on ESS are valued at more than US$11.1 billion per year (17.94% of GDP) - too high a cost to ignore. Were Uzbekistan and its development partners to invest $2.9 billion over 10 years to implement recommended packages of policy, institutional, and technological innovations to combat ARD, the country would reap returns worth $47.9 billion at a benefit-cost ratio of 16.5.

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1. Introduction

Different kinds of lands and soils provide ecosystem services (ESS) that contribute to human wellbeing by performing several functions. These include provisioning (e.g. food and water), regulating (e.g. climate regulation and water purification), and cultural services (e.g. recreation and aesthetic values), while their indirect benefits include supporting services including pollination, soil formation and erosion control (MEA, 2005; Daily et al., 2000). Each of these services plays a vital role in achieving the United Nations Sustainable Development Goals (MEA, 2005; Naderi and Fallahi Akhlamad, 2025; Nedd and Anandhi, 2024; Peng et al., 2021; Cochran et al., 2020; Nkonya et al., 2016; de Groot et al., 2012). At the same time, land degradation is happening at an alarming rate (Luck et al., 2009) due to natural and anthropogenic causes, including poor management of natural capitals such as soils, water, and vegetation. This leads to soil erosion, nutrient depletion, salinity, water scarcity, pollution, disruption of biological cycles, and loss of biodiversity (Critchley et al., 2021; Pereira, 2020; IPBES et al., 2018). These processes, in turn, affect peoples' current livelihoods and their sustainability, notably by threatening the supply of food and water, degrading the quality of living environments, and reducing biological diversity (Naderi and Fallahi Akhlamad, 2025) which underpins the variety of genes, species, and ecosystems—and their functional interactions (Naeem et al., 2009). For detailed synthesis of the evidence on how ecosystem services, biodiversity, and resilience to climate change are interconnected, and identification of pathways for integrating these dimensions into sustainable management and policy, refer to (Naderi and Fallahi Akhlamad, 2025). Lad degradation (LD) is globally widespread and is estimated to severely or moderately affect about 52% of agricultural lands in all regions of the world, thereby costing up to USD 10.6 trillion or USD 1,450 per person per year (ELD, 2015). A recent study documented that 40% of the planet's land is already degraded, which directly affects half of humanity and threatens roughly half (US$44 trillion) of global GDP (UNCCD, 2022). Soil erosion stands out as a particularly economically significant consequence of LD because it undermines agricultural productivity (through the loss of nutrient-rich topsoil), disrupts ecosystems, and contributes to water reservoir sedimentation (Abiye, 2022; Nathan et al., 2022).

Inaction on LD can result in costly and sometimes irreversible damage. The United Nations Convention to Combat Desertification announced that the time has come for the international community to commit itself to a LD neutral world by setting sustainable development goals on land-use, with targets towards achieving LD neutrality (UNCCD, 2012). With intentional action and targeted investments, a suite of mitigation measures has been shown to curb and at times reverse LD. For example, sustainable land management (SLM) practices have high potential to reduce rates of LD and help to ensure water security by increasing soil moisture availability, decreasing surface runoff, decreasing soil erosion, increasing infiltration, and decreasing flood discharge (Dagnachew et al., 2024). To motivate investment, create conducive policy and institutional environments, and unlock funding for implementing such innovations, decision makers need reliable estimates of the ESS lost due to inaction, the benefits of interventions, and their associated monetary values. Such efforts help in creating awareness among society and decision makers on the gravity of the problem, the cost to current and future generations, and the returns on investment to combat LD.

In view of the local, national, and international efforts to combat LD, robust frameworks are needed to: (1) quantify the scale of the problem; (2) calculate the cost of inaction or business-as-usual, and (3) assess the costs and benefits of restoration (Sutton et al., 2016). Different approaches exist to estimate various LD indicators including expert opinion, satellite derived net primary productivity (NPP), biophysical models, and abandoned croplands (Gibbs and Salmon, 2015). Several past studies mainly rely on the estimation of changes in NPP, and ecosystem service values induced by LD arising from land-use, land cover, and land management changes (Talukdar et al., 2020; Elias et al., 2019; Bai et al., 2019; Kindu et al., 2016; Kronenberg, 2014). Different biome- or commodity-based ecosystem models exist including G-Range (Sircely et al., 2019) for rangeland ecosystem modelling, FATES (Fisher et al., 2015); LANDIS PRO Harvest (Wang et al., 2015); aDGVM (Scheiter and Higgins, 2009) for forest ecosystems modelling, Ecopath with Ecosim (Christensen and Walters, 2004), and Atlantis (Fulton et al., 2011) for marine and fisheries ecosystems.

Models used for the quantification and valuation of ESS include the InVEST model [(Naderi and Fallahi Akhlamad, 2025); (Natural Capital Project, 2025; Dashtbozorgi et al., 2023a; Yang et al., 2018)], value transfer method - VTM (UK, 2011), emergy analysis model (Zhan et al., 2019), the SECAS framework to form a unified conceptualization for outdoor recreation (Morse et al., 2013), and cost-based methods (Plummer, 2009). See (Bagstad et al., 2013) for an in-depth review of decision support tools for ecosystem services quantification and valuation. Other tools developed to aid our understanding of the changes in different natural capitals, the tradeoffs among them, the forms and magnitudes of degradation taking place in these valuable resources, and their implications for human well-being include the SWAT model (Arnold et al., 1998), remote sensing-based radiation use efficiency (RUE*)* models (Helman and Bonfil, 2022; Prince and Goward, 1995), and the InVEST suite of models (Zhang et al., 2025; Sharp et al., 2014; Van Remortel et al., 2001).

Several past studies employed one or more of the above and/or similar approaches to make landscape- (Mengist et al., 2022; Metzger et al., 2021), national- (Bukvareva et al., 2019; Jia et al., 2014; Carreño et al., 2012), continental- (Jamouli and Allali, 2020; Maes et al., 2012), and global-level [(Cochran et al., 2020); (Sutton et al., 2016); (Brander et al., 2024a)] estimates of different ESS lost due to inaction. However, only a few deal with the valuation of these resources, estimation of costs of degradation, and returns on investment to restore these resources. One of the most widely used such models is the InVEST model [(Sharp et al., 2014); (NCP, 2026)] which provide GIS-based spatially explicit solutions has been widely used for the quantification and/or valuation of land-use and land cover (LULC) changes and the associated fluctuations in carbon stock (Legesse et al., 2024; Li et al., 2024), degradation of natural capitals in agriculture (Seeboonruang et al., 2025; Gashaw et al., 2021), threats to biodiversity and reduction in the quality of habitats (Dashtbozorgi et al., 2023b; Kija et al., 2020), and their implications on the quantities and values of ecosystem services and hence human wellbeing at local, national, and regional levels in different parts of the world (see (Mukhopadhyay et al., 2025) for a systematic review). There are also few other models including the SEEA Ecosystem Accounting model (King et al., 2024), the model developed by (Yet et al., 2020) to provide decision support for project evaluation under different risk scenarios, the bio-economic farm model called Multi-Objective Decision Support Tool for Agro-Ecosystem Management (MODAM) that has the capability of estimating the shadow prices of ESS from which demand and supply curves can be derived (Prato et al., 1996).

While primary data on experiments and model results can provide the necessary parameters for the quantification of ESS, their monetization requires the use of economic valuation methods (Cordier et al., 2014a). Ecosystem valuation, especially for such natural capitals as biodiversity and their socio-ecological benefits, can be a difficult and controversial task, and economists have often been criticized for trying to put a price tag on nature (Costanza et al., 2017; Schröter et al., 2014). However, investment decisions aimed at conserving and preventing the degradation of natural resources typically involve limited budgets and tradeoffs, as these resources may yield higher opportunity costs and/or returns if invested elsewhere. Therefore, economic valuation can help justify and prioritize programs, policies, or actions that contribute to the protection or restoration of ecosystems and their services.

Climate change is exacerbating the global challenge of ARD (Cosmas et al., 2025) making it imperative for governments and their national and international development partners to make important policy and

investment decisions to combat it. To this effect, evidence on costs of inaction to combat ARD such as the magnitudes and monetary values of ESS being lost which shows the gravity of the challenge needs to be generated at different scales and in a way that is palatable to policy and investment decision makers.

Two limitations stand out in the existing tools and methods for quantification and valuation of ESS. First, most of these tools and methods involve sophisticated models which are very complex to replicate and hence there is a lack of consistent and comparable estimates across biomes, geographies, and LD classes. Secondly, ecosystem- or commodity-specific models that do not address the whole spectrum of LDtoESStoeconomic values provide only partial evidence, thereby falling short of providing sufficient policy and investment guidance (Mandle et al., 2021).

In this paper, we aim to contribute to addressing the inherent limitations of existing tools and methods on both fronts by 1) developing a simple Excel-based tool which is intuitive, and user friendly to provide actionable information. 2) ensuring evidence on important pieces of information, namely, the costs of inaction to show the scale of the problem, the benefits of action and the cost of implementing the needed interventions, and the returns on investment - thereby answering most questions raised by policy makers and hence inducing changes in policy and (Sutton et al., 2016).

The primary objective of this paper is to propose a decision support tool called "Analysis Pack for Economics of Agricultural Resource Degradation and Ecosystem Service Losses (APEARD)" for economic analysis of ARD. APEARD is composed of three modules which, together, enable the quantification and valuation of ESS lost/gained due to inaction/action, the cost of implementing a suite of optimal policy, institutional, and technological interventions identified for specific countries/provinces, and ultimately the returns on investment for combating LD. The tool provides all the above estimates for all four biomes in agriculture (crop lands, forest lands, natural pastures, and irrigation water). To aid priority setting for investment, APEARD also has the capability to generate all these estimates for each of the three land degradation classes (low, moderate, and severe) that are established for each biome based on objective criteria. Spatially, APEARD is versatile as it can be applied at different geographic levels including three administrative levels (district, province, and country), or at a watershed or landscape level. As a proof of the versatility and capability of APEARD, we also present, in this paper, results from a case study of Uzbekistan in which the tool was applied.

2. Methods

In the quest for providing complete information that can guide policy and investment decisions, we followed Statistics Canada's environmental and resource accounting system (SC, 2014; Prudham and Lonergan, 1993) and developed a tool which comprises three separate but complementary modules, each, serving specific purposes. From the outset, we disclose, here, that the methodological contribution of this paper is one of presenting a simple decision support tool (APEARD) which systematically compiles and aggregates data and parameter estimates generated from various published and unpublished sources, remote sensing, and expert estimates and applies simple mathematical logic to define equations that quantify ESS and widely used economic valuation methods to monetize them. Fig. 1 presents the methodological framework of APEARD.

The guiding principles in the development of APEARD are: 1) It should be simple requiring no sophisticated modelling skills so that anyone with basic knowledge of ecological and economic concepts can use it; 2) the estimates generated by it need not be accurate, but good

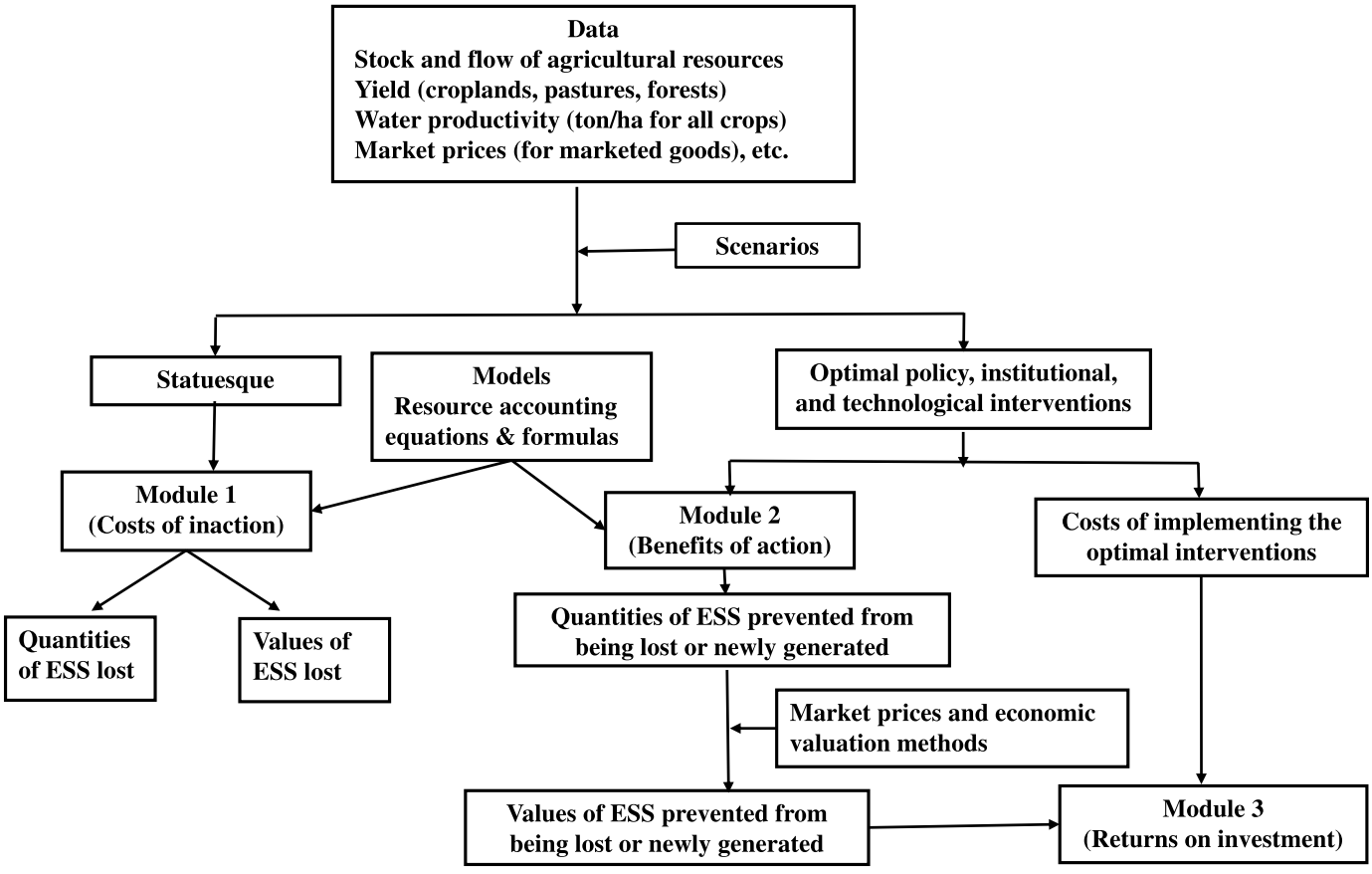


Fig. 1. Methodological framework of APEARD.

enough to indicate the minimum quantities and values of ESS lost/gained, which themselves, are often large enough, to induce investment and policy changes; 3) the approach should be consistent and standardized to enable spatial and temporal comparisons; 4) the estimates must be generated at different scales, if possible, starting from district, if not at province levels and must be amenable for aggregation to national, regional, and global levels; and 5) while using a ten-year planning horizon for investment to combat ARD, to derive the message home, the estimation should focus on the flows rather than the stocks of resources and hence the estimates should refer to a single year and monetary values presented both in absolute terms (converted into their net present values using proper discounting factors) and as percentage of national (or provincial) GDP.

For developing APEARD, we followed the following steps. First, we classified the two natural capitals in agriculture (land and water). Land was further classified into three (cropland, pastureland, and forest). Depending on the diversity of crops cultivated in a country, croplands were further classified into different sub-categories (cereals, legumes, vegetables, fruits, cultivated forage, etc.). Natural pasturelands were also classified into pastoralist lands, agro-sylvo-pastoralist lands, and prairies as appropriate. Water resources were also classified into two (surface and ground water). Second, based on (Gregersen et al., 1995), we classified the total value of agricultural resources into two broad categories, namely use and non-use values. These categories are further classified leading to a total of 12 final classifications. Third, we identified the ESS associated with each of the final classifications under the two natural capitals in agriculture. Fourth, we made decisions on methods to estimate the quantities of ESS lost/gained using simple and intuitive concepts, and simplifying assumptions needed to make these estimations. Fifth, we defined costs of inaction, benefits of action (or interventions), and prices as follows:

1) **Costs:** We defined costs of inaction as the quantities/values of ESS that are being lost due to lack of intervention to control LD. For quantifying ESS loss due to LD, we classified all lands into three (low, moderate, and high) degradation classes and assumed the differences between crop/pasture/forest lands with low degradation and those in lands with moderate and high degradation represent the quantity of ESS lost due to LD per unit of land. For example, applying the yield-gap concept (Van Ittersum et al., 2013), the yield lost due to LD in lands with severe degradation is defined as the difference between average yield in lands with low degradation and that in lands with severe degradation. Then, we applied market prices of the respective crops to monetize the quantified ESS that are lost.
2) **Benefits:** Benefits of action (or interventions) are defined as the quantities and values of ecosystem services that are prevented from being lost (or newly generated) by intervening to restore agricultural resources (land, water, and forest). As in the case in costs, the differences between the benefits of interventions in lands with low degradation and in moderate/severe degradation are assumed to represent the benefits of interventions in moderate/severe lands.
3) **Prices:** For valuation of the costs and benefits, while we have used market prices for valuation of marketed ecosystem services (such as lost wood due to deforestation, and carbon emission due to erosion or additional carbon sequestered due to afforestation), following the discussions in (Tilahun et al., 2018; Cordier et al., 2014b), we used mainly the opportunity cost method for non-marketed ESS (such as soil eroded, and water lost). For soil loss for example, we made a simplifying assumption that its use value is the sum of the value of grain (and straw for cereals and legumes) biomass yield, the value of carbon that was sequestered in soil but emitted due to erosion and estimates of the income from tourism and educational services. Due to the complexity of pricing, non-use values are not omitted from the current version of APEARD.

Sixth, we defined the mathematical equations that are needed to determine the quantities of interest. Finally, market and non-market prices (Tilahun et al., 2018; Cordier et al., 2014b) were used for valuation of the quantities of ESS estimated. Sections 2.1-2.3 below provide more detailed description of the approaches and mathematical relationships used.

Data on several variables needed for APEARD are generated from various sources including secondary data from literature, experiments, official (published) and unpublished statistics. Wherever applicable, we also used remote sensed data. In the absence data for some variables from the above sources, however, as an option of last resort, we used estimates by a multidisciplinary team of experts.

2.1. Description of APEARD

APEARD consists of three modules. The first module estimates the quantities of ESS lost due to inaction and their monetary values. The second module estimates the monetary costs of action (i.e. the costs of implementing a suite/package of optimal policy, institutional, and technological interventions in each biome/crop category that are identified to be effective in combating LD) and their benefits in terms of avoided losses of ESS or newly gained ESS due to action, in both biophysical and monetary terms. The third module calculates the returns on investment in the form of a benefit: cost analysis. The length of the planning horizon (ten, twenty, thirty, or any other number of years) is chosen depending on the availability of good climatic projections and the optimal time for exploiting full economic and ecological values of the investment (for example, equipment that are purchased and the crops and trees planted). To make current and future monetary values comparable, net present values are used, where costs and benefits are discounted over time into their dollar equivalents for a specific year.

We follow (Gregersen et al., 1995) to classify the total value of land resource into two broad categories: Use and non-use values (Fig. 2). Use values are further classified into direct and indirect use-values. Direct use values are again classified into consumptive and non-consumptive use values. Consumptive use-values include ecosystem service values that are produced on the land for immediate consumption (such as grain and straw on crop fields, wood and timber on forest lands, hay, and leafy biomass from pastures) and services that are used indirectly (such as irrigation water that is used for producing crops). Non-consumptive use-values refer to recreational, educational and research values. Indirect use values are classified into the following four categories: (i) Watershed management, soil protection, and nutrient recycling; (ii) gas (carbon dioxide and oxygen) exchange, carbon storage, and climate stabilization; (iii) habitat and protection of biodiversity and species; and (iv) aesthetic, cultural and spiritual values. As discussed in (Chan et al., 2013; Oglethorpe and Miliadou, 2000), non-use values of natural resource or environmental assets are classified into three broad categories: (i) Option values (values of the option of not using it in the present time); (ii) existential values (values of its mere existence); and (iii) bequest values (the value of the ability to bequeath it to future generations).

APEARD helps in the generation of consistent and comparable estimates of inaction and benefits of action, and the returns on investment to combat LD in each of the four important biomes in agriculture: crop lands, natural pastures, forests, and water (i.e. for irrigation). It also estimates associated damages in infrastructure and LD-induced health problems for each LD class x biome x sub-national (e.g., province) combination. These data are ultimately aggregated to national levels using appropriate area and production weights. To assist in targeting interventions, crop lands in APEARD are further disaggregated into lands planted with different crop groups (cereals, legumes, vegetables, fruits, and cultivated forages). While it omits some important ESS due to complexity of estimation and data problems, APEARD provides estimates of different ESS including food (specifically for cereals, legumes, fruits, vegetables, and cultivated forages), forages from natural pastures, forest biomass, soils, water, and carbon emissions. The tool can be

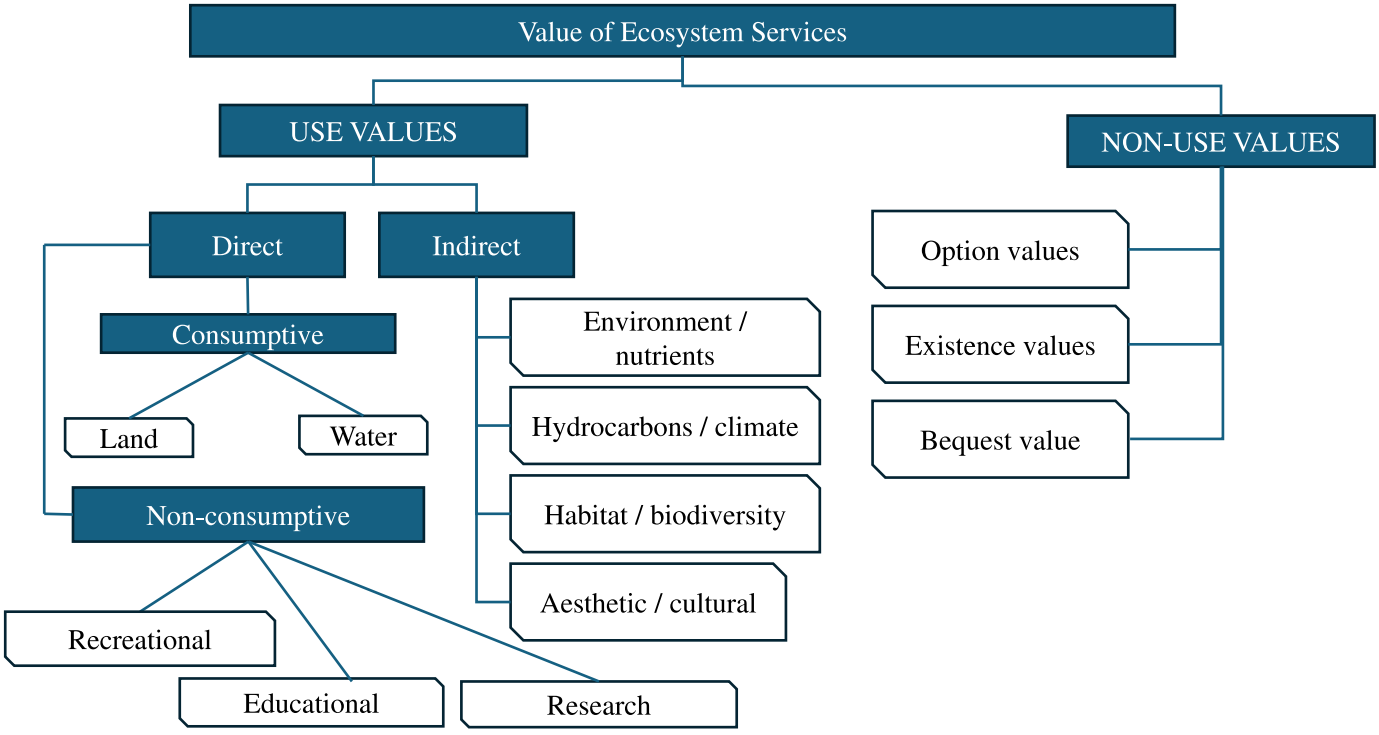


Fig. 2. Classification of values of ecosystem services as per (Gregersen et al., 1995).

adapted to carry out analysis at landscape, province, LD-class, national, or any other level.

2.2. Costs of inaction

The first module of APEARD was developed for estimating the costs of resource degradation and the associated LD-induced damages in infrastructure and health problems. APEARD estimates ESS lost due to inaction by classifying agricultural land based on its degradation state, estimating productivity losses by comparing the degraded state biomass with potential biomass, and estimating the total economic cost of such losses. First, total agricultural land is divided into crops, forest, and natural pastures and then classified based on their level of LD. The estimation of LD levels involves the integration of multiple indicators, including vegetation condition, soil exposure, and soil salinity. Values of these indicators were derived as averages of ten-year data obtained from the Landsat-8 satellite images. To evaluate vegetation conditions, we used the Normalized Difference Vegetation Index (NDVI) which measures the amount and vigor of vegetation on the land surface. As a proxy for soil exposure, we used albedo, which is a measure of the ability of surfaces to reflect light or heat from the sun. For soil salinity, we used the salinity index which is derived from the reflectance values in the blue (B) and red (R) bands (Bannari et al., 2008). We used Principal Component Analysis (PCA) to combine the three indices, which is a linear dimensionality reduction technique to capture the largest variation in the data. The resulting combined land degradation index (CLDI) was then used to classify the land under each biome into the three distinct (low, moderate, and severe) LD classes. The PCA-based classification process was augmented by the Jenks natural breaks optimization technique (Jenks, 1967) for clustering, which aims to minimize variance (or average deviation) within each LD class while maximizing the variance between (or across) the three LD classes.

After the three LD classes are established, the next step is to assemble information on the biomass yield per unit area (e.g. per ha) of land under biome *i* classified as having LD level of *j* in province *p* (BY_{ijp}). Depending on the biomes included and the production system under consideration, this can be yield of grains, vegetables, or fruits and other useful biomass including forage crops which can be obtained from field or plot-level surveys. The total volume of woody biomass that can be harvested from a forest land (keeping in mind the total allowable cut in the area) and total amount of hay and other forage material that can be harvested from a pastureland per unit area would preferably be obtained from physical measurements. These data points should be collected under the current policy, institutional, and technological (including management) environment. If primary measurement data is not available, this information can be generated from remote sensing, literature review, simulation models, official statistics, records, and/or expert elicitation.

Typically, estimates of ESS losses due to LD are based on comparisons with a scenario of no degradation as counterfactual. This implicitly assumes that after the intervention, the natural capital will be restored to its full (100%) potential (Quillérou et al., 2016). We argue that these assumptions are not realistic because: 1) it is difficult, if not impossible, to know the attributes of natural capital if degradation had never taken place (the counterfactual); 2) interventions may not restore the natural capital to its original state and, hence, the benefits of action and the costs of inaction may be overestimated (Quillérou et al., 2016). Therefore, in APEARD we assume that ecosystem services generated in the low degradation class is the highest one can expect in each biome. With this assumption, for example, we apply the yield-gap concept (Van Ittersum et al., 2013) and use the biomass yield in crop lands classified as "low degradation" as the reference yield, i.e., the yield level in lands with low LD class is the highest attainable yield under current conditions. Therefore, the magnitude of LD-induced biomass yield loss (in tons) for biome *i* in a land with degradation level *j* in province *p* (BYL_LD_{ijp}) is computed as the difference between biomass yield in lands with *Low* degradation in province *p* ($BY_{i,LOW,p}$) and biomass yield in lands with degradation level *j* in province p (BY_{ijp}) (where *j* represents moderate and sever degradation levels):

$$BYL_{LD\,ijp} = BY_{i,LOW,p} - BY_{ijp} \quad (1)$$

This means, biomass yield loss in land with *Low* degradation in province *p* ($BYL_LD_{i,LOW,p}$) is assumed to be zero, while biomass yield

loss in severely degraded lands will be the highest and that in moderately degraded lands will be somewhere in between the two.

Once the LD-induced biomass yield loss per unit area (BYL_LD_{ijp}) is estimated, then the total amount of LD-induced biomass loss (in tons) from biome i in a land with degradation level j in province p ($TLBP_{ijp}$) can be computed as the product of: 1) the share (in %) of each degradation level j in total area of biome i in province p (AS_{ijp}); 2) total area (in hectares) of biome i in province p (A_{ijp}); and 3) the LD-induced biomass yield loss per unit area (in tons) (BYL_LD_{ijp}):

$$TLBP_{ijp} = AS_{ijp} * A_{ip} * BYL_LD_{ijp} \quad (2)$$

In cases where multiple products or commodities are produced (for example grain and straw from wheat), then the same procedure should be applied to generate the value lost in each product or commodity type:

$$TLBP_{ijpc} = AS_{ijp} * A_{ip} * BYL_LD_{ijpc} \quad (3)$$

Where, BYL_LD_{ijpc} represents the LD-induced biomass yield loss per unit area for commodity c of biome i in land with degradation level j in province p.

The same procedure is also used for estimating LD-induced loss in other ESS such as soil erosion and carbon emissions. For irrigation water loss, we use estimates of annual provincial total water supply from surface and ground water sources (in cubic meters) as the starting point. Then, data on average conveyance losses during water distribution (at primary, secondary, and tertiary canals) are distributed across all crop lands as there is no reason to believe that they vary across the three LD classes. On farm irrigation water loss due to runoff and evaporation is assumed to be the highest in lands with severe and moderate degradation while it is least in the low degradation class. Therefore, estimates of average on-farm water loss (due to runoff, evaporation, poor irrigation practices, and low adoption of available technologies) in the low LD class is used as the reference (counterfactual) for the moderate and severe LD classes. Likewise, for rainwater loss due to runoff, estimates are generated using hydrological models, data from experimental stations, or secondary data from literature for each LD class and the estimates for the low LD class are used as the counterfactual values.

For estimating the total economic costs of LD, we use market and non-market valuation methods to attach monetary values to the estimates of each of the ESS lost due to inaction described above. Full description and conceptualization of the total economic cost of LD (TEC_LD) due to inaction in the APEARD model is provided in Annex II of (Yigezu et al., 2020).

2.3. Benefits of action

Yield data needed for models such as APEARD (including the interaction effects of multiple technologies on yield) do not exist, especially in the developing world. As a result, crop growth models, which also require a lot of data for calibration and validation, are often used. To minimize errors in assembling this large dataset, APEAR starts with assembling available data from literature and from unpublished experimental studies. Then, multi-disciplinary teams of experts are required to identify optimal packages of policy, institutional, and technological innovations for each LD class X biome/crop category X province combination (which hereafter are referred to as target combinations). The experts are also required to fill the gap in estimates of current adoption levels for the different combinations of technolgies, from which APEARD automatically estimates total area for each target combination that requires investment and the associated cost for applying the optimal package of policy, institutional, and technological innovations. Then, based on cost data from past projects and efforts, APEARD guides the experts to make estimates of the total cost of implementing these packages of interventions per unit area in each combination (CI_{ijp}) which are then aggregated to the cost of intervention by LD class (CI_j), by biome (CI_i), by province (CI_p), and ultimately to the national level (CI) which is computed as:

$$CI = \sum_{ijp} CI_{ijp} \quad (4)$$

This estimate represents the total cost of implementing the full innovation package to combat LD in the total national area (or in the prioritized areas, if prioritization is made). The next step is to estimate the benefits of action (i.e., the benefits of implementing the optimal innovation packages) which are described in detail below.

2.3.1. Estimation of gains in direct use values

While there could be some data from field surveys or experimental stations on the impacts of some of the individual technologies (or some combination of them), the impacts of introducing the full policy, institutional, and technological innovation package are often not known. The third module of APEARD provides estimates of the percentage biomass yield gains that are expected if the full innovation package was to be implemented in each target combination. This starts with available data on yield gains due to the implementation of one or more of the components of the innovation package. Then, multidisciplinary team of experts is tasked to extrapolate yields for the combinations of innovations for which data is lacking. After costs of inaction are calculated, APEARD estimates the gains in direct use values due to implementation of the full innovation package in each biome, as well as the avoided damage to infrastructure and avoided health problems caused by natural disasters (such as floods, sand, and dust storms, etc.). The calculation proceeds as follows.

The total economic gain due to action (TEG_A) in a country is given by:

$$TEG_A = \sum_{p=0}^{P} TEG_A_p \quad (5)$$

Where TEG_A_p is total economic gain due to action in province p (where provinces can be replaced by any other geographic unit such as districts, landscapes, zones, regions etc. as appropriate), where p represents provinces and P is the total number of provinces. TEG_A_p is estimated as:

$$TEG_A_p = TEG_AB_p + TEGO_A_p \quad (6)$$

Where TEG_AB_p and $TEGO_A_p$ are total economic gains in biomass and cost savings from avoided infrastructure damage and health problems, respectively, due to implementation of the innovation package. These are calculated as follows:

$$TEG_AB_p = \sum_{i=0}^{I} TEG_AB_{ip} \quad (7)$$

$$TECO_A_p = \sum_{k=0}^{K} TEGO_A_{kp} \quad (8)$$

Where TEG_AB_{ip} is the total economic gain due to action in biome I in province p, $TEGO_A_{kp}$ is total economic gain due to prevention in category k of one of the other LD-induced problems (infrastructure damage, health problem, natural disaster, etc.) in province p, and I and K represent the total number of biomes and the number of other LD-induced problem categories considered.

APEARD also requires the multidisciplinary team to estimate the share (in %) of each degradation level j in total area of biome i in province p (AS_{ijp}) based on official statistics, secondary data, remote sensing, expert estimates, or a combination of any two or more of these sources where $\sum_{j=0}^{v} AS_{ijp} = 100\%$. Then, total economic gain due to action in biome i in province p ($GTEC_AB_{ip}$) can be computed as:

$$TEG_AB_{ip} = \sum_{j=0}^{J} AS_{ijp} * TEG_AB_{ip} \quad (9)$$

where J = the total number of levels of LD, which in our case is 3 (low, moderate, and severe).

To compute the total value of gain due to action in the production of commodity c in a given biome type *i* in lands with degradation level *j* in province *p* (TVG_AB_{ijpc}) APEARD requires estimates of biomass yield gained (in percentage) due to action in commodity c in biome type *i* in lands with degradation level *j* in province *p* ($PERYG_AB_{ijpc}$). These estimates can be taken from experimental data, past research, or simulation modelling. Following the approach of (Pearce and Markandya, 1987) for valuation of the social cost of natural resource depletion, we use the concept of marginal opportunity cost (MOC) to estimate the total economic gain as the value of the additional production obtained through preventing or reversing LD. Therefore, APEARD computes the total value of gain due to action in land which is used for the production of commodity c in biome *i* characterized by a degradation level of *j* in province *p* (TVG_AB_{ijpc}) as the product of the percentage biomass yield gain in commodity c, the average biomass yield in commodity c in biome type *i* in lands with degradation level *j* in province *p* (BY_{ijpc}), and the price for commodity c in biome type *i* in US$ per ton in province *p* (PB_{ipc}):

$$TVG_AB_{ijpc} = PB_{ipc} * PERYG_AB_{ijpc} * BY_{ijpc} \quad (10)$$

The choice of price for each product (commodity) will depend on the final use of the specific product. For example, in the case of wheat in Uzbekistan, both the grain and straw are produced predominantly for local consumption, therefore average prices of wheat grain and wheat straw in the local markets were used. However, if wheat grain in a particular province is produced for export purposes, then the export price would be used. In some cases, a certain percentage of wheat grain produced in a province may be exported while the remaining is consumed locally, in which case the average provincial price should be computed using the local and export market shares as weights. Then, APEARD computes the total economic gains in production of biome *I* in a land categorized as having degradation level *j* in province *p* ($TEGBP_{ijp}$) as the sum of the total value of gains due to action in production of commodity c in each biome *i* in lands with degradation level *j* in province *p,* mathematically:

$$TEGBP_{ijp} = \sum_{c=1}^{C} (TVG_AB_{ijpc}) \quad (11)$$

For national aggregation by biome and LD class, the total national economic gain due to action in land which has degradation level of *j* used for the production of biome *i* (TEG_AB_{ij}) is calculated as the sum across all provinces of the total economic gain due to action in land used for the production of biome *i* which has degradation level of *j* in province *p* (TEG_AB_{ijp}), i.e.,

$$TEG_AB_{ij} = \sum_{p=1}^{z} TEG_AB_{ijp} \quad (12)$$

In addition to the gains in biomass production in agriculture, action to combat LD can also lead to the prevention from damage of infrastructure including roads (paved, unpaved, and local or secondary), bridges, railroads, airport runways, irrigation infrastructure, telephone, and electricity poles, and other assets such as buildings, trees, human life, domestic and wild animals (Hewett et al., 2018).

To generate estimates of the total economic gain from avoided damage/destruction of category *k* of another LD-induced problem in province p ($TEGO_A_{kp}$), we use similar concept but slightly different approach (as in equation (5) above) than that used for the gain from action in land under different biomes as described in equation (4). The approaches used for estimation of total economic gain from the prevention of land-degradation-induced damage/destruction in each specific type of asset are described below.

2.3.1.1. Transportation infrastructure. Total avoided losses from the prevention of LD-induced destruction of category k in transportation infrastructure (including roads, rail roads, airport runways) in province p ($TEGO_A_{kp}$ (*Trans_infra*)) are computed as the sum of total economic gain from the prevention of LD-induced damages/destruction on all transportation infrastructure types t in province p ($TEGO_A_{tp}$), i.e.,

$$TEGO_A_{kp}(Trans_infra) = \sum_{t=1}^{T} TEGO_A_{tp} \quad (13)$$

Where T is the total number of types of transportation infrastructure considered.

For this calculation, APEARD requires the following data (either for a typical year by taking long term average value or a particular year for which estimates are needed). Description of the following list of needed data assumes that estimates are being generated for a particular year under consideration.

1) Total length (in km) of each type of transportation infrastructure t including paved roads, unpaved roads, local (secondary) roads, railroads, and airport runways in each province p (TTI_{tp});
2) Percent of the total length of each transportation infrastructure type t that is prone to LD-induced damages in each province p in the year under consideration ($PTID_{tp}$);
3) Percent of the total length of each transportation infrastructure type t that is prone to LD-induced damages in province p in the year under consideration that can be prevented from being damaged through action on LD ($PTIPD_A_{tp}$);
4) Average repair cost (in US$/km) for infrastructure type t in province p which was damaged in the year under consideration but can be repaired ($ACRKM_{tp}$);

Then, the total economic gain of action to prevent LD-induced damages on all transportation infrastructure type t in province p ($TEGO_A_{tp}$) mentioned in equation (12) can be computed as the product of items 1-4 in the above list, i.e.,

$$TEGO_A_{tp} = PTID_{tp} * PTIPD_A_{tp} * TTI_{tp} * ACRKM_{tp} \quad (14)$$

2.3.1.2. Other infrastructure. A similar approach as the one described above for transportation infrastructure can also be used to estimate avoided damages in other infrastructure and assets such as irrigation canals, buildings, electric and telecommunication poles, fallen trees, vehicle breakage or overturning due to bad roads, etc. When length in km is not applicable, physical quantities, number of units, areas, etc. and hence the costs should also be adjusted to be per unit of the item in reference.

2.3.1.3. Natural disasters (emergencies). Actions to combat LD can also prevent or decrease the frequency of weather-related natural disasters including land sliding, snow avalanches, rock falling, mud flows and heavy floods (Hewett et al., 2018; Kato and Huang, 2021). These are different from the avoided losses of infrastructure damage discussed above, which refer to minor incidents that happen at different magnitudes and scales every year. Conversely, natural disasters happen more rarely, and the locations affected can vary from year to year. Moreover, the damages associated with natural disasters are of large magnitude, often requiring full replacement/reconstruction of the assets damaged. Therefore, cost estimates require long-term data so that average annual costs can be computed and thereby costs can be averaged across all the years under consideration.

The same procedures used for estimating the total avoided losses to transportation infrastructure due to action can also be used to estimate avoided losses from LD-induced natural disasters in province *p* ($TEGO_A_p$ (Nat_disa)). The only change will be that this category refers to extreme disasters and hence the damage is often irreparable, and the

assets are destroyed. Therefore, we use costs of total replacement, reconstruction, or rebuilding. The data required are:

1) Total quantity of assets type (a) destroyed in the last ten years in province p ($TQAD_LD_{ap}$).[1] This includes total length (in km) or number, or area (in m^2 or Km^2), or quantity, etc. of each type of asset (a) including paved roads, unpaved roads, local (secondary) roads, railroads, airport runways, irrigation canals, residential, business, hospital, school, etc. Buildings, trees, vehicles, domestic and wild animals, etc. That were completely destroyed or killed in each province p;
2) Average cost (in US$/per unit) of replacing (reconstructing) the asset type (a) which were destroyed in province p in the last ten years ($ACRCPU_{ap}$).

Then, the total annual economic gain due to action to prevent LD-induced disasters for asset a in province p ($TEGO_A_{ap}$ (Nat_disa)) can be computed as the product of items 1 and 2 above divided by the number of years for which data has been collected (in the case of Uzbekistan, we considered ten years), i.e.,

$$TECO_LD_{ap}(Nat_disa) = \frac{TQAD_LD_{ap} * ACRCPU_{ap}}{10} \quad (15)$$

Finally, the avoided losses due to action to prevent all types of damage due to LD-induced natural disasters in province p ($TEGO_A_p$(-Nat_disa)) can be computed as:

$$TEGO_A_p(Nat_disa) = \sum_{a=1}^{A} TEGO_A_{ap}(Nat_disa) \quad (16)$$

Where A is the total number of asset types.

2.3.1.4. Health problems. LD also leads to loss of soil that can easily be blown into the air by wind. The most pronounced of this is when dust- and sandstorms are created, causing air pollution, leading to respiratory tract-related sicknesses including allergies and asthma among children and adults and associated deaths (Kato and Huang, 2021; Moos et al., 2018; UNCCD, 2025; Castelli et al., 2023; Bodor et al., 2024; Behzad et al., 2018). Ideally for landscape-level analyses, results from sophisticated dispersion models, remotely sensed spatial distribution of annual average particulate matter ($PM_{2.5}$),[2] and district-level mortality databases for air pollution-related diseases and the associated statistical lives lost would be used to generate precise estimates of benefits of action to prevent LD-induced health problems. This method was used when APEARD was applied for a case study of the Aralkum area of Uzbekistan (De Longueville et al., 2013). However, given the complexity, and large amounts of data needed, and hence the implied time required to process these data for national level studies, more simplified and indirect estimation of these costs is considered as a better option, especially for developing countries where data and resources are scares. For example, data can be collected from the provincial health departments on the number of people treated for respiratory problems, estimates of the percentage of such sicknesses caused by air pollution related to dust and sandstorms, and the average treatment cost per patient of respiratory problems due to dust and sandstorms. The product of these gives an estimate of the total cost of dust-related health problems, given the current levels of LD.

There are also other forms of LD-related health problems including those caused by contamination of water bodies by agricultural chemicals and industrial waste. Estimation of such costs is often complex and requires detailed study and is thus outside the scope of the current version of APEARD.

For the estimation of total economic gain in the prevention of LD-induced health problems, we use the same concept described above where the prevented cost of treatment for people sick from LD-induced diseases is used as a proxy measure. To this effect, the following information will be needed:

1) The total number of people in province p who contracted sickness types (s), such as upper respiratory problems, stomach issues, and other health conditions potentially related to, but not necessarily caused by, land degradation (TPS_LDsp) in the year under consideration serves as a proxy for prevention potential.
2) Share (in percentage) of LD-induced health problems in total cases of sickness of type (s) in province p ($SLDS_{sp}$);
3) Average cost of treating an incidence of LD-related sickness type (s) per person in province p in US$ (ACT_{sp});

Then, the estimate for total economic gain due to action to prevent LD-induced sickness of type (s) in province p (TEG_APS_{sp}) can be computed as the product of items 1-3 above, i.e., $TEG_APS_{sp} = SLDS_{sp} * TPS_LD_{sp} * ACT_{sp}$ (17).

I total economic gain due to action to prevent LD-induced health problems in province p (TEG_APS_p) can be computed as the sum across all sickness types s of the economic gains from prevention of LD-induced sickness of type (s) in province p (TEG_APS_{sp}), i.e.,

$$TEG_APS_p = \sum_{s=1}^{S} TEG_APS_{sp} \quad (18)$$

2.3.2. Indirect use values

2.3.2.1. Soil and water. LD in crops, forests, and pasture lands also causes losses in indirect use values which include watershed and soil protection, nutrient recycling, gas (carbon dioxide/oxygen) exchange, climate stabilization through carbon storage, protection of habitats and associated plant and animal biodiversity, and aesthetic, cultural and spiritual values. Gains in these indirect use values due to action can be estimated per unit area of land with the different LD classes. Then the total avoided losses to indirect use values can be calculated following the same procedures as described above for direct use values. Measuring measurements of most of the indirect use values are, however, very complex requiring sophisticated soil, agronomy, and hydrological models as in (Lelieveld et al., 2020), economic values of pollinator-dependent yield, and biodiversity. Which are not easy to estimate, and data on tourism, hunting, and recreation revenues, which are often inaccessible. As a result, in the current version of APEARD, only the cost of LD-induced loss in soil and the associated carbon emission is estimated.

While the amount of soil that is eroded for each LD class by biome by province is estimated, it is noteworthy here that the cost of soil degradation including soil erosion, soil salinity, and sodicity are not explicitly valued but indirectly valued through the loss of biomass production in moderately and highly degraded lands relative to lands with low land degradation. Enteric methane emission from livestock is also not explicitly included but indirectly accounted for in the estimation of carbon emission from forage and crop residue disposals. The same procedure as in the estimation of total economic gain from the prevention of LD-induced loss of biomass is used here, except that instead of the total biomass that can be produced under each level (i) of LD, here we use the total amount of carbon that is sequestered above- and below-ground in land with degradation level of (i). The global price of carbon is

[1] Due to the complexity of attaching dollar values to human life, the cost of people killed due to natural disasters may be left but the number of people who lost their lives due to land-degradation-induced problems should be mentioned in the report.

[2] It is becoming evident that $PM_{2.5}$ contributes to the incidence of cardiovascular and respiratory diseases, and potentially to premature death (Akramkhanov et al., 2021).

used in place of the market price for the biomass/product.

2.3.2.2. Service disruption due to infrastructure damage. When infrastructures and other assets are damaged, the services and uses they provide are interrupted. For example, when a road is damaged, the number of trucks, cars and people that can commute will reduce or be completely halted depending on the level of damage. Therefore, estimates of avoided losses to such economic benefits are estimated. For example, for a damaged road it would be necessary to estimate the number of people who become absent from work, goods and services that are not brought to the market and are spoiled, economic values that are not generated, etc. Government ministries often have estimates of the cost of interruption per day per km of different road classes and scales of damage. Then, the product of these per unit costs and the lengths (in km) of total damaged roads by scale of damage would provide an estimate of the total value of services prevented from being lost due to LD-induced damage to assets and infrastructure.

2.3.2.3. Health problems. When people are sick due to LD-induced problems, they either must stay at home or be hospitalized during which they cannot work. As a result, the economic implications of action to prevent LD-induced health problems can be approximated as the product of the average number of days the typical patient with sickness type (s) misses work and his/her average daily salary/wage. The total indirect value of preventing LD-induced health problems can be estimated by multiplying this value with the total number of LD-induced patients in the province.

2.3.2.4. Natural disasters (emergencies). During LD-induced emergencies and natural disasters, transportation and other services are interrupted, and people get sick and become absent from work. Generating estimates of the economic costs from such disruptions is difficult, however government emergency and disaster management offices may have estimates of such disasters. Such offices can also estimate the share of LD in total emergencies of natural disasters (SND_p). The total economic gain from the prevention of disruptions in services due to LD-induced natural disasters in province p ($TIEG_LD_p$ (Nat_disa)) can then be computed as the product of the share of LD in total disasters (SND_p) and the total economic cost of all disruptions due to natural disasters in province p ($TIEG_p$ (Nat_disa)), i.e.,

$$TIEG_LD_p(Nat_disa) = SND_p * TIEG_p(Nat_disa) \quad (19)$$

the costs of implementing a suite of optimal policy, institutional, and technological interventions in each biome/crop category to combat LD.

3. An application of APEARD - a case study from Uzbekistan

All three modules of APEARD were applied at different scales in Uzbekistan -at landscape level for only the Aralkum basin area (De Longueville et al., 2013), only for the severely degraded lands in all biomes, crop categories, and provinces (Vogl et al., 2024), and at national level covering all LD-classes, provinces, and biomes/crop categories (Yigezu et al., 2023). To demonstrate the capability of APEARD, we present below results of the national level analysis for Uzbekistan (Yigezu et al., 2023).

In the application of APEARD for the case of Uzbekistan (Yigezu et al., 2023), we used the parameter values presented in Tables A1–A10 in the supplementary material to this article. For estimation of ESS lost due to degradation in soils, a simplified approach that utilizes an index combining levels of soil erosion by water and wind, level of salinity, and mobile nitrogen, phosphorus, potassium, humus and other variables was used. We classified the total area (for crops, natural pastures, and forests) and total amount (for water) of each biome in each province into three LD levels, namely low, moderate, and severe. As shown in Table A1 in the supplementary material to this article, we adapted (Yigezu et al., 2023b) and classified erosion levels of less than 5 ton/ha as slight, between 5 and 20 ton/ha as low; between 20 and 40 ton/ha as moderate, and above 40 ton/ha as severe erosion. However, as most of the natural forest and shrublands are located on higher slopes, we chose to classify these differently to be more conservative in what is considered degraded to avoid confounding slope effects with degradation. Consequently, we used the following cut off points for classifying soil erosion in forests: low: <40 t/ha, moderate: 41-80n t/ha; and high: >80 t/ha. A composite index of erosion and other soil properties (see Tables A1–A5 in the supplementary material to this article) is then used to classify the lands into the low, moderate, and severe degradation classes.

3.1. Costs of inaction

Uzbekistan has a total land area of 44.9 million ha of land which is composed of 3.9 million ha of crop lands (8.6%), 21.2 million ha of natural pastures (47.3%), 3.4 million ha of forests (7.7%), and 16.4 million ha (36.4%) of other land-use types including settlements, water bodies, infrastructure, etc. Using extremely conservative assumptions, an application of APEARD estimated that Uzbekistan is annually losing at least 2.6 million tons of potential production of different crops (including cereals, legumes, cotton, vegetables, and fruits), which represents 6.9% of current production and the associated crop residues in one season (Table 1). Degradation also causes the loss of 63.8 thousand tons of forest and shrub biomass (0.04% of total stock), and 477 thousand tons (9.15%) of forage from natural pastures. Moreover, due to inaction or inadequate action to conserve water and reduce losses, the country is losing at least 18.2 billion cubic meters of water or 39.5% of total supply (Table 2). We also estimated that the country is losing at least 194 million tons of soil (i.e., 4.32 ton/ha or 0.1% of total soil stock) every year due to erosion (Table 3), which is also associated with the release of at least 1.6 million tons of carbon into the atmosphere. In addition to these losses, the country is suffering different kinds of harm (including health, infrastructure damage, extreme weather, water, and soil salinity, abandoned farmlands, etc.) related to degradation of the natural capitals in the agriculture, forest, and water sectors [(Singh et al., 1992); (De Longueville et al., 2013); (Khasanov et al., 2023)], for which no detailed estimation is provided in this report. The monetary value of these ESS that are being lost is at least US$11.1 billion per year which is equivalent to 17.94% of the GDP of Uzbekistan (Table 4).

3.2. Benefits of action and returns on investment

Based on the severity of LD, 3.3 million ha (87%) of national crop lands, 2.7 million ha (13%) of natural pastures, 0.6 million ha (16%) of forests, i.e., a total of 6.6 million ha (i.e., 23%) of agricultural lands were prioritized by the research team for intervention. Introduction of the optimal policy, institutional, and technological changes in the prioritized 6.6 million ha of agricultural lands is expected to generate additional production 5.7 million tons (i.e., 15.2 % of current production in one season) of food and non-food crops (including cotton), 11.1 million tons of forest and shrub biomass (6.7 % of total stock), and 907 thousand tons of forage (i.e., 17% of current production). The recommended changes will also prevent the loss of 9.1 billion cubic meters of water (19.7% of total current supply) and the erosion of 106 million tons of soil (55% of the estimated erosion level under inaction) and hence emission of 858 thousand tons of carbon. The interventions will also conserve 330 thousand tons of diesel from reduced tillage operations, 455gw of electricity from pumping irrigation water, and 174gw of electricity from conditioning greenhouses, with a combined reduction of 285 thousand tons of carbon emissions. The monetary values of all the ESS prevented from being lost or newly gained due to action in the prioritized 6.6 million ha of agricultural lands is estimated at US$8.1 billion (equivalent to 13.1% of GDP).

Considering a planning horizon of ten years, the cost of

Table 1
Minimum amount of production (tons) lost annually due to land degradation by crop type, by province, and national aggregates in Uzbekistan.

Province	Total annual production losses (tons) due to land degradation by crop type:							Provincial Total	As % of total national	Loss in ton per ha of crop land
	Cereals	Legumes	Cotton	Potatoes	Vegetables	Fruits	Other crops			
Andijan	25,846	978	6121	10,315	43,798	19,491	41,530	**148,079**	**5.63%**	0.03
Bukhara	41,393	617	22,942	17,212	56,971	39,304	83,449	**261,888**	**9.95%**	0.08
Fergana	38,433	1913	19,653	24,654	83,275	41,850	50,184	**259,962**	**9.88%**	0.07
Jizzakh	59,233	3397	19,664	6604	34,040	9371	47,643	**179,953**	**6.84%**	0.08
Xorazm	39,249	319	36,743	14,920	69,099	22,860	69,157	**252,347**	**9.59%**	0.11
Namangan	25,607	2481	13,241	19,261	55,194	27,603	27,873	**171,260**	**6.51%**	0.06
Navoiy	19,914	563	6120	4524	15,850	10,476	28,412	**85,859**	**3.26%**	0.07
Qashqadaryo	65,119	788	29,445	14,459	39,895	20,814	54,335	**224,854**	**8.54%**	0.08
Samarqand	37,051	5278	21,721	61,828	142,997	88,960	41,113	**398,948**	**15.16%**	0.08
Sirdaryo	33,377	3032	12,901	4280	19,150	3762	59,803	**136,305**	**5.18%**	0.08
Surxondaryo	43,826	1607	13,902	20,631	61,820	16,207	55,975	**213,968**	**8.13%**	0.06
Tashkent	25,052	669	14,273	21,863	59,776	12,579	30,164	**164,377**	**6.25%**	0.05
Karakalpakstan	28,202	750	7749	8237	27,350	6565	55,101	**133,954**	**5.09%**	0.09
Total Uzbekistan	**482,302**	**22,391**	**224,476**	**228,789**	**709,213**	**319,843**	**644,740**	**2,631,754**	**100.00%**	0.07
Crop loss in ton per ha of land	**0.03**	**0.00**	**0.01**	**0.14**	**13.45**	**0.30**	**6.91**	**0.77**		
Share of each crop in total crop loss (%)	**18.33%**	**0.85%**	**8.53%**	**8.69%**	**26.95%**	**12.15%**	**24.50%**	**100.00%**		
Rank	**3**	**7**	**6**	**5**	**1**	**4**	**2**			

Source: authors' own estimation

Table 2
Amount of water (in million cubic meters) lost due to inaction to control degradation in irrigation water resources.

	Province	Annually lost water (million M^3) by source:				Percentage share of each loss point in total water lost annually			Annually lost water (million M^3) due to:			
		Surface water resources	Ground water resources	Total	Loss as % of total supply	Conveyance losses	Storage losses	Field-level losses	Conveyance losses	Storage losses	Field-level losses	Total
1	Andijan	875.25	13.30	888.55	38%	61%	34%	5%	538.28	302.11	48.16	888.55
2	Bukhara	1874.64	27.84	1902.48	47%	50%	42%	8%	948.77	799.04	154.67	1902.48
3	Fergana	1282.19	33.23	1315.41	41%	56%	36%	8%	741.76	473.55	100.10	1315.41
4	Jizzakh	725.72	9.92	735.64	26%	73%	23%	4%	535.40	169.20	31.04	735.64
5	Xorazm	1717.97	-	1717.97	45%	52%	39%	9%	891.11	670.01	156.85	1717.97
6	Namangan	1101.88	18.99	1120.87	35%	63%	31%	6%	704.69	347.47	68.71	1120.87
7	Navoiy	604.74	16.81	621.55	44%	54%	39%	7%	332.82	242.40	46.32	621.55
8	Qashqadaryo	1855.77	30.60	1886.37	35%	64%	32%	4%	1201.37	603.64	81.36	1886.37
9	Samarqand	1447.21	16.85	1464.05	40%	58%	36%	6%	843.00	527.06	93.99	1464.05
10	Sirdaryo	949.44	4.13	953.56	29%	70%	25%	5%	663.49	238.39	51.68	953.56
11	Surxondaryo	1134.24	6.47	1140.71	40%	56%	34%	10%	641.65	387.84	111.22	1140.71
12	Tashkent	1399.63	5.24	1404.87	37%	61%	34%	5%	853.88	477.66	73.33	1404.87
13	Karakalpakstan	2995.88	-	2995.88	49%	47%	44%	9%	1406.27	1318.19	271.43	2995.88
	Total Uzbekistan	**17,964.55**	**183.38**	**18,147.92**	**40%**	**57%**	**36%**	**7%**	**10,302.50**	**6556.55**	**1288.88**	**18,147.92**

Source: authors' own estimation

implementing the full package of optimal policy, institutional, and technological innovations was estimated at US$2.9 billion. If Uzbekistan and its national and international development partners were to make this investment, the country can expect to obtain benefits which are valued at US$47.9 billion (in 2023 US$ equivalents) in 10-years - leading to high returns on investment represented by an average benefit-cost ratio of 16.52 (Tables 5 and 6). Sensitivity analysis was conducted on the discount rate and carbon prices. While model results showed modest increases of 26% and 42% in BCR in response to about 50% and 75% reductions in the discount rate, respectively, the responses to ±25% change in carbon price had negligible (±0.31%) effect on BCR (see Tables A9 and A10 in the supplementary material). These results show that future applications of APEAR must report the results of the sensitivity analysis, especially on discount rates.

4. Discussion

In the past decade, a notable increase in demand for information on the economic value of ecosystem services to improve the conservation and management of natural capital was observed from both public and private institutions. To meet this demand, there is a need for targeted and refined valuation research to ensure sufficient certainty, comparability, and representativeness of the data, and to enable transferability and fill knowledge gaps (Brander et al., 2024b). However, the existing models for estimation of the values of ESS have limited use for policy makers for several reasons including: 1) they involve sophisticated models that are not palatable to most policy makers; 2) they provide either incomplete information in terms of the indicators (e.g., only monetary costs of inaction without the corresponding magnitudes of ESS being lost), or limited spatial and temporal coverage. Such incomplete results fail to convince policy makers of the seriousness of the issue, its geographic distribution, and its relative intensity thereby making these results less useful in priority setting for investment. Ecosystem- or commodity-specific models that do not address the whole spectrum of LD-to-ESS-to-economic values provide only partial evidence, thereby falling short of providing sufficient policy and investment guidance

Table 3
Minimum amount of soil (tons) lost annually due to erosion by biome/crop type, by province, and national aggregates in Uzbekistan.

	Province	Total soil erosion (ton) in Uzbekistan												As % of total crop loss	As % of total loss in all biomes	Loss (ton per ha) of total land area
		Cereals	Legumes	Cotton	Potatoes	Vegetables	Fruits	Other crops	Forests and shrubs	Permanent Pastures (grass lands)	Other lands	Total for all crops	Total for all biomes			
1	Andijan	275,835	4525	253,730	27,314	71,444	104,802	72,839	53,803	180,350	548,008	**810,490**	**1,592,651**	**6.36%**	**0.82%**	**3.70**
2	Bukhara	195,048	2449	293,122	17,278	53,582	39,138	118,853	2,946,553	7,582,984	2,379,968	**719,469**	**13,628,974**	**5.64%**	**7.02%**	**3.39**
3	Fergana	411,325	5881	296,500	41,684	89,278	193,895	95,904	238,631	118,231	1,169,920	**1,134,467**	**2,661,249**	**8.90%**	**1.37%**	**3.94**
4	Jizzakh	854,187	55,646	287,720	9140	40,845	68,910	218,156	3,504,064	2,996,942	2,944,318	**1,534,604**	**10,979,928**	**12.04%**	**5.66%**	**5.18**
5	Xorazm	277,435	3528	348,033	18,605	49,963	49,904	119,769	549,754	305,546	775,777	**867,236**	**2,498,313**	**6.80%**	**1.29%**	**4.13**
6	Namangan	300,481	8139	227,654	24,779	46,238	110,603	64,583	307,002	724,771	1,153,537	**782,477**	**2,967,787**	**6.14%**	**1.53%**	**3.99**
7	Navoiy	129,022	1877	97,681	7899	15,612	32,775	42,632	17,016,982	41,038,497	2,497,591	**327,497**	**60,880,567**	**2.57%**	**31.37%**	**5.48**
8	Qashqadaryo	709,233	15,853	394,309	18,224	40,425	55,292	126,734	5,060,081	8,068,559	2,261,138	**1,360,071**	**16,749,849**	**10.67%**	**8.63%**	**5.86**
9	Samarqand	595,917	43,353	241,633	50,415	113,046	141,059	242,062	184,740	3,576,762	1,455,860	**1,427,486**	**6,644,849**	**11.20%**	**3.42%**	**3.96**
10	Sirdaryo	275,644	3925	209,267	5580	17,417	17,896	56,971	50,773	92,907	584,027	**586,699**	**1,314,406**	**4.60%**	**0.68%**	**3.07**
11	Surxondaryo	311,170	2931	200,759	27,928	48,461	134,990	107,417	3,404,883	3,248,266	1,681,160	**833,656**	**9,167,965**	**6.54%**	**4.72%**	**4.56**
12	Tashkent	629,888	17,727	346,223	39,757	110,957	159,713	254,008	1,330,304	2,195,496	3,037,973	**1,558,271**	**8,122,044**	**12.22%**	**4.18%**	**5.21**
13	Karakalpakstan	302,494	13,652	259,490	20,140	48,306	18,486	142,622	11,991,301	14,272,565	29,809,029	**805,190**	**56,878,086**	**6.32%**	**29.31%**	**3.41**
Total Uzbekistan		**5,267,680**	**179,486**	**3,456,120**	**308,742**	**745,575**	**1,127,464**	**1,662,548**	**46,638,870**	**84,401,878**	**50,298,307**	**12,747,614**	**194,086,669**	**100.00%**	**100.00%**	**4.32**
Loss (ton per ha) of total land in this biome		**3.31**	**3.40**	**3.25**	**3.31**	**3.35**	**3.35**	**3.33**	**13.58**	**3.97**	**3.07**	**3.30**	**4.32**			
Share of each crop in total soil loss (%)		**2.71%**	**0.09%**	**1.78%**	**0.16%**	**0.38%**	**0.58%**	**0.86%**	**24.03%**	**43.49%**	**25.92%**	**6.57%**	**100.00%**			
Rank		**4**	**10**	**5**	**9**	**8**	**7**	**6**	**3**	**1**	**2**					

Source: authors' own estimation

Table 4
Estimates of the minimum monetary value of ecosystem services lost due to inaction (in US$).

Type of Value	Cost (in million US$) of land degradation per year:							
	In all crop lands	In natural forests	In natural pastures	Water	In abandoned crop lands	Infrastructure damage and economic losses induced by extreme weather and emergency	In the form of health problems	Total (US $/year)
1. Use value	2,078,230,904	17,668,156	126,253,381	6,574,166,282	1,571,254,212	475,748,274	38,255,206	**10,881,576,414**
1.1 Direct use value	2,050,354,346	2,183,342	23,107,104	6,574,166,282	1,571,254,212	475,748,274	22,953,123	**10,719,766,683**
1.2 Indirect use value	27,876,558	15,484,814	103,146,276	-	-	-	15,302,082	**161,809,731**
2. Non-use value	150,837,753	-	355,618	2,609,647	-	-	38,255,206	**192,058,224**
Total	**2,229,068,657**	**17,668,156**	**126,608,999**	**6,576,775,930**	**1,571,254,212**	**475,748,274**	**76,510,411**	**11,073,634,638**
As a % of GDP	**3.61%**	**0.03%**	**0.21%**	**10.66%**	**2.55%**	**0.77%**	**0.12%**	**17.95%**

Source: authors' own estimation

Table 5
Total 10-year discounted benefits of action.

Item/Province	Crops	Water	Natural Pastures	Forests (Assuming average annual allowable cut of 10% of total stock)	Prevention of landslides & flooding, and reduction of LD-induced health problems	Total value of benefits of action (US$)
Andijan	1,961,801,303	2,117,706,131	765,360	675,306	26,353,531	**4,107,301,632**
Bukhara	1,906,732,517	1,939,027,699	23,257,655	56,524,085	38,886,678	**3,964,428,633**
Fergana	2,787,406,984	3,309,645,559	985,748	2,893,724	45,351,520	**6,146,283,535**
Jizzakh	1,825,936,772	817,518,462	12,239,027	32,929,728	18,481,062	**2,707,105,051**
Xorazm	1,507,154,263	693,764,581	1,852,551	11,137,514	18,853,194	**2,232,762,103**
Namangan	2,227,840,108	1,663,668,213	2,447,640	4,131,019	49,563,838	**3,947,650,818**
Navoiy	876,721,546	1,080,332,003	125,151,573	214,699,466	31,231,789	**2,328,136,377**
Qashqadaryo	2,313,438,005	1,609,602,428	22,515,405	33,249,728	42,130,393	**4,020,935,959**
Samarqand	3,464,625,575	1,020,243,331	15,302,435	2,550,888	56,483,408	**4,559,205,637**
Sirdaryo	1,544,294,894	1,483,377,418	347,661	709,091	16,408,292	**3,045,137,355**
Surxondaryo	2,829,984,922	1,298,793,385	13,221,590	46,482,822	77,110,638	**4,265,593,359**
Tashkent	1,931,851,301	2,148,734,840	8,350,849	15,157,373	68,668,081	**4,172,762,443**
Karakalpakstan	901,603,891	1,222,529,408	69,915,507	181,350,393	26,702,960	**2,402,102,160**
Total Uzbekistan	**26,079,392,081**	**20,404,943,460**	**296,352,999**	**602,491,138**	**516,225,384**	**47,899,405,061**
Share of each biome or component in total benefits	**54.45%**	**42.60%**	**0.62%**	**1.26%**	**1.08%**	**100.00%**

Source: authors' own estimation

(Mandle et al., 2021); 3) they don't provide returns on investment in a way that comparison across biomes, space, and competing projects is possible; and 4) most of them are not amenable to (or at best difficult for) adaptation to other locations making it difficult to generate large figures the kinds of which draw the attention of policy makers.

Table 6
Benefit:cost ratio of investment to combat resource degradation in agriculture.

Province	Crops	Water	Natural Pastures	Forests	Total for all Biomes
Andijan	36.19	20.36	5.04	5.79	**25.92**
Bukhara	12.80	12.16	3.01	5.64	**12.16**
Fergana	33.56	31.24	4.89	6.62	**32.41**
Jizzakh	35.82	7.46	5.51	6.72	**16.14**
Xorazm	13.67	8.32	5.62	6.93	**11.42**
Namangan	21.04	18.88	5.40	5.78	**20.22**
Navoiy	16.59	40.25	4.67	5.65	**16.11**
Qashqadaryo	12.05	11.41	5.31	6.77	**11.75**
Samarqand	14.48	9.25	6.37	6.56	**12.94**
Sirdaryo	19.50	15.43	5.79	5.64	**17.35**
Surxondaryo	43.79	13.02	5.31	6.66	**24.53**
Tashkent	12.70	24.74	6.21	6.21	**17.19**
Karakalpakstan	11.33	12.41	4.41	5.65	**10.63**
Total Uzbekistan	**21.96**	**15.66**	**4.61**	**5.86**	**16.57**

Notes: 1) BCR for forests is low because the benefits of forests are not fully realized in 10 years; 2) BCR for pastures is low because the current productivity of natural pastures is very low and we have made a very conservative assumption of yield gains.

The development and improvements of APEARD have taken considerable time (about three years) and resources. However, experience has shown that, depending on data availability, its application to specific case studies can be completed in as short a time as six months which, given the amount of information it generates, can be considered impressive.

Looking at the Uzbekistan case study, results generated by APEARD were highly appreciated by the government officials in the country and its international development partners such as the WB. Some of the results were even included in the WB flagship report "Climate Development Report of Uzbekistan". We believe that such high interest was created because unlike other models and methods applied in the past, APEARD was able to generate both the magnitudes and values of ecosystem services lost/gained due to inaction/action in one year, at different administrative levels (provinces, and national), and for all four biomes in agriculture, and in a way that allows comparison to GDP. We believe that these results will aid in creating more awareness on the magnitudes of ESS services being lost and the associated cost of inaction, and in alerting on the urgency of combating agricultural resource degradation (ARD) and hopefully in inducing changes in policy and investment decisions.

5. Conclusions

This paper developed a tool (APEARD) for carrying out an analysis of the economics of resource degradation in agriculture. The tool supports

the estimation of ecosystem services that are being lost due to low or inadequate action, as well as the value of services that can be prevented from being lost or newly generated by implementing optimal packages of policy, institutional, and technological innovations. It also helps to estimate the total cost of implementing the optimal package of innovations and to estimate the discounted value of benefits that can be generated throughout the planning horizon and ultimately the returns on investment. APEARD provides all these estimates at provincial levels and uses area figures as weights for upward aggregation to national levels.

APEARD provides a framework for making consistent estimates within and across biomes/crop categories, and across landscapes, countries, regions, and might ultimately provide the basis for more consistent and reliable global estimates that can be updated at certain time intervals as needed. Such estimates will provide sufficient information (both in terms of quantities of ESS and monetary parameters) for priority setting for investment by governments, the private sector, financial institutions, and national and international development partners. It will also be useful in creating awareness on the magnitudes of losses incurred due to inaction and the benefits that can be obtained from action thereby helping prioritize investment decisions for combating LD.

One or more of the three modules of the APEARD tool (though not known as such then) have been applied in the past to the cases of Tajikistan, Uzbekistan, and Tunisia and there is an ongoing effort for its application to the case of Ethiopia. The evidence generated so far has been an eye opener for policymakers in those countries and has helped in creating awareness on the gravity of the economic, biophysical, and environmental impacts of resource degradation in agriculture. For example, some of the results of the APEARD model have been included in the World Bank's flagship report "Uzbekistan Country Climate and Development Report" and the estimated costs of inaction have influenced a high-level panel of government officials in Tunisia to request the development of a large project to combat ARD. These two examples illustrate the importance of the comprehensive information that is generated by the APEARD tool.

CRediT authorship contribution statement

Yigezu A. Yigezu: Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Akmal Akramkhanov:** Writing – review & editing, Validation, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Adrian Vogl:** Writing – review & editing, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Abeyou Worqlul:** Writing – review & editing, Validation, Software, Methodology, Investigation, Formal analysis. **Akmaljon Ganiev:** Writing – review & editing, Validation, Investigation, Data curation. **Azaiez O. Belgacem:** Writing – review & editing, Validation, Investigation, Data curation. **Aziz Nurbekov:** Writing – review & editing, Validation, Investigation, Data curation. **Elena S. Golub:** Writing – review & editing, Validation, Methodology, Investigation. **Haitham Bahri:** Writing – review & editing, Validation, Investigation, Data curation. **Jorge E.L. Sarmiento:** Writing – review & editing, Validation, Software, Investigation, Data curation. **Meriem Barbouchi:** Writing – review & editing, Validation, Investigation, Data curation. **Mira Haddad:** Validation, Software, Methodology, Investigation, Data curation. **Mohamed Annabi:** Writing – review & editing, Validation, Investigation, Data curation. **Mounir Louhaichi:** Writing – review & editing, Validation, Investigation, Funding acquisition, Data curation. **Paola Agostini:** Writing – review & editing, Validation, Methodology, Investigation. **Serge M. Piabuo:** Writing – review & editing, Validation, Methodology, Investigation. **Stephen Strohmeier:** Writing – review & editing, Validation, Methodology, Investigation, Data curation. **Tanzila Ergasheva:** Writing – review & editing, Validation, Project administration, Investigation, Data curation. **Umidjan Nazarkulov:** Writing – review & editing, Validation, Investigation, Data curation.

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Appendix A. Supplementary data

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Data availability

Data will be made available on request.

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