

Valuing Fishing Access on Lake Victoria's Winam Gulf: A Hedonic Pricing Model

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ABSTRACT

Economic values for fish access and water quality of lake resources can help validate and prioritize conservation measures, facilitate natural resource planning efforts, and inform benefit-cost analyses of improved fishing projects. This research uses the hedonic pricing method (HPM) to investigate values for proximity to major fishing docks, and a composite water quality measure, in the Winam Gulf area on Lake Victoria in East Africa. HPM statistically decomposes variation in owner-occupier housing sale prices and separately in rent prices to isolate marginal implicit prices for the access and quality measures. The analysis uses the 2012/2013 Kenya National Household Survey (KNHS), and a water quality index measured for 12 major fishing docks on Winam Gulf in Kenya. ArcGIS is used to measure the distance from fishing docks to the center of sub-locations. Log-linear econometric modeling results indicate that closer proximity to fishing docks positively affects property values by \$1804.24 per kilometer for housing sale prices and \$854 per kilometer for annual house rent prices. Although reductions in composite water quality are a rising concern in the Winam Gulf region, water quality is not yet capitalized in either house sale prices or rental rates.

Keywords: Hedonic Pricing Model, fishing access, water quality index, Winam Gulf, hedonic property values, fishing docks, marginal implicit price

JEL classification number: Q5

Mathematics subject classification: 91B76 and 91B18

1. INTRODUCTION

Freshwater lakes provide various ecosystem goods and services, many of which are not fully captured or directly reflected in market prices (Tarnian et al. 2020). For instance, many communities proximal to the various lakes in sub-Saharan Africa, including Lake Victoria, the largest, remain heavily

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dependent on fishing as a source of livelihood; thus, they indirectly depend on both levels of water quality that can sustain this fishing and the access or transportation means to the fishing docks. Measuring the total economic value (TEV) connected to the various water quality protection and road access improvement projects for different lakes in sub-Saharan Africa is an ongoing challenge because of the lack of adequate formal data and the developing state of economic systems³ (Berner 2001; Delaire et al. 2017). Although competitive fish markets may offer evidence on the fish catch and respective fish price, they may not fully reflect the TEV of ecosystem services that a lake provides to surrounding communities.

Measuring economic values for the different components of lake resources can support conservation measures by informing benefit-cost analyses and natural resource planning. A substantial body of economic research attempts to fully value lake resources in developed countries using various nonmarket valuation techniques. The battery of available techniques includes survey-based stated preference approaches such as the contingent valuation method and revealed preference approaches, such as travel costs models and hedonic pricing models of nearby housing values (Nicholls and Crompton 2017; Tuttle and Heintzelman 2015). However, limited studies focus on sub-Saharan Africa or the values related to communities dependent on commercial fishing and water quality protection. This lack of valuation of lake resources is consonant with the region's lax or absent conservation policies. Many lakes in sub-Saharan Africa face increasing water pollution from industrial wastes motivated by economic incentives (Scheren, Zanting, and Lemmens 2000) and the poor management of spreading invasive species such as water hyacinth on Lake Victoria. Kateregga and Sterner (2009) associate the low prioritization of conservation measures and road maintenance to the low fish catch affecting livelihoods and the increased risks of food insecurity in lake-surrounding communities (Kateregga and Sterner 2009).

The twin challenges of poor water conservancy and road access networks are significant on Lake Victoria in Kenya. With a surface area of 68,800 km², this Lake is the second-largest freshwater and largest tropical globally (Swallow et al. 2009). It supports the largest inland fishery in Africa, provides water for domestic and industrial use, and serves as a regional transport system across Tanzania, Kenya, and Uganda⁴. In particular, the livelihoods of Lake-edge communities on the Winam Gulf on the Kenyan shores of Lake Victoria heavily depend on fishing (Opande, Onyango, and Wagai 2004). Despite this, human waste released into the Lake, alongside the water hyacinth invasive species, may be reducing the value of the Lake to riparian towns (Taabu-Munyaho et al. 2016).

Additionally, the six counties adjacent to the Lake have poor road infrastructure connecting to the fishing docks. Recent research has begun to explore these interactions (Ibrahim and Ramzy 2013;

³ The economic system in sub-Saharan Africa is characterized by a large informal sector, and high unemployment rates (Jackson 2012).

⁴ Over 40 million people consume fish from Lake Victoria (Nyamweya et al. 2016)

Jiwyam 2014). For example, Nyamweya et al. (2016) used the Atlantis ecosystem modeling framework to consider Lake Victoria's ecosystem's biophysical, economic, and social aspects. However, the analysis lacks a complete set of economic values for this water resource.

Using the hedonic pricing method (HPM), this research investigates observed variation in housing sale prices and rents. It isolates any effects from residential proximity to major fishing docks and corresponding composite water quality measures in the Winam Gulf area on Lake Victoria. HPM involves econometrically modeling the price or rent of any heterogeneous good, such as residential property, to isolate the value of one or more environmental attributes while controlling for other attributes or characteristics (Taylor 2017). In this case, the estimated values or marginal implicit prices represent the marginal willingness to pay for proximal access to fishing docks and/or water quality, as provided by lake cleanup programs, paving murram roads, and extension programs from the community-based environmental conservancy.

The HPM application analyzes house characteristics from six counties in Kenya bordering the Winam Gulf. Winam Gulf is a significant extension (more than 40km) of Lake Victoria, with a narrow inlet averaging 25km wide. The survey data from the Kenya National Household Survey (KNHS) is combined with water quality data at 12 major fishing docks on Winam Gulf based on (Orina, Onyango, Lungayia, Andrew Oduor, et al. 2020). ArcGIS mapping software identifies the proximity of housing sublocations to the nearest fishing docks. Notably, the water quality index is designed using a weighted arithmetic index (Shivanna and Nagendrappa 2015) from sample analysis of these fishing docks and includes the temperature, turbidity, PH values, Secchi, total dissolved solids, biochemical oxygen demand, and conductivity.

Econometric results show no statistical evidence that water quality significantly affects either house sales values or house rental prices. These results are likely due to the lack of variation in our water quality measure across the 12 sites or the lack of recognition by current household residents (i.e., it is not yet being capitalized in prices or rents). However, in contrast, econometric results indicate that closer proximity to fishing docks positively affects marginal implicit prices (in 2020 US dollars) by (i) \$1804.24 per kilometer (or 1.36 percent) for the average house property sale value reported in our sample; and (ii) \$854 per kilometer (or 23.23 percent) for the average annual house rental value reported in our sample. The former (i) represents the increment to the capitalized present value of proximity in a house sale, but the latter (ii) is an annual rent increment. If the latter were paid out for, say, just five years and discounted back to the present value (at a 5% discount rate), it would represent \$2440.31 (or 2.81 percent) for the average house property sale value as reported in our sample. Thus, results support the hypotheses that both house buyers and renters are willing to spend more on houses for fishing access, but renters are willing to pay significantly more in present valued terms.

2. BACKGROUND

2.1 Water Quality and House Prices

Fish catch on Lake Victoria depends on the water quality levels at the fishing docks (Ranta, Lindström, and Rask 1992). Measuring the effect of this quality can be done using nonmarket valuation methods, as categorized into stated and revealed preference methods (Carruthers and Clark 2010). Stated preference methods require primary surveys to undertake choice experiments or contingent valuation approaches, which rely on hypothetical questions. Alternatively, revealed preference methods such as the hedonic price method and travel cost method typically rely on secondary data (but can also come from survey data), which portrays participants' choices that reflect the implicit value of environmental characteristics (Taylor 2017).

Empirical evidence suggests that lake water quality affects the prices of properties surrounding the Lake (Bin et al. 2017; Papenfus 2019). Houses are heterogeneous goods whose characteristics can be decomposed into consumer demand preference attributes, including access to environmental ecosystems. According to Gibbs et al. (2002), lake water clarity increases residential property prices. In a six-year panel study in New Hampshire in the United States (US), they find that a one-meter change in clarity affects four real estate market areas differently. This study demonstrates that protecting water quality is mirrored in surrounding property values and property tax revenues. Papenfus (2019) finds similar results while looking at water quality impairments on residential housing prices using data from Washington state in the US. For example, they show that a house adjacent to an impaired waterbody depreciates annually by \$1942.

One challenge in the hedonic analysis includes identifying an appropriate water quality metric. Market participants are unlikely to fully understand or observe scientific measures. However, homebuyers can quantify water quality impacts at ecological endpoints such as fishing docks affected by observable invasive species or/and their respective fish catch. Several papers look at clarity, acidity, fecal coliform, dissolved oxygen, temperature, and PH values in hedonic price models on residential properties (Bin et al. 2017; Papenfus 2019; Walsh et al. 2017). According to Papenfus (2019), the US Environmental Protection Agency uses a process of assessing water bodies using characteristics on turbidity, toxic substances, temperature, total phosphorus, PH, dissolved oxygen, and bacteria. These characteristics are essential in this study because they inform the supply of the main fish species in the Winam Gulf: *tilapia* and *Nile perch*.

2.2 Hedonic Property Value

Apart from the water quality impact, some studies have looked at the corresponding distance to real estate properties. In particular, some studies have investigated whether cleanup activities and policies positively affect hedonic property valuation estimates. In a meta-analysis study on the Chesapeake Bay, Klemick et al. (2018) use the mean of water clarity of homebuyers and transfer the

benefit to other Chesapeake bay neighboring counties. A meta-analysis synthesizes multiple estimates across several studies. Findings show that pollution cleanup efforts translate to property values along with the water source. Near water-front property values could increase by \$400-\$700 million in response to a water clarity improvement project. Since our analysis for the Winam Gulf on Lake Victoria relies on hedonic property value analysis, it reflects on the necessity of obtaining the marginal implicit price that homebuyers place on the adjacent property to adequately control for the impact of cleanup initiatives. For example, given the general case of low cleanup activity on Lake Victoria, results might show a low but positive marginal implicit value.

Homebuyers and renters' marginal implicit price on houses next to Lake Victoria might embody a willingness to pay to acquire increased fishing access. This willingness to pay considers the use-value for fishers, fish consumers, and indirect use-values for tourists, lake transit commuters, and local empowerment groups. In a quest to identify the impact of the water hyacinth invasive species, Opande et al. (2004) surveyed visitors on beaches along the Winam Gulf on Lake Victoria. Their results showed negative impacts of the invasive species were highest on boat owners, fishers, and fish consumers. Respondents cited low fish catch due to a high level of hyacinth blocking their entrance and exit to the Lake, interfering with fish transportation, and destroying fishing gear. Other concerns from the invasive species included increased malaria, encephalitis, gastrointestinal disorders, and other diseases. The economic value of harvesting water hyacinths for energy and agricultural resources remains unclear.

2.3 Fishing Access and Infrastructure

The land use along the fishing docks has residential, industrial, commercial buildings, road networks, open grounds, and vegetation. Communities on the lake shores access Lake Victoria primarily by road, sometimes traveling long distances (Njiru et al. 2008). Although some bays on Winam Gulf, such as Kisumu Bay have a rail system in place, it is mainly non-operational due to wear-and-tear. Similarly, roads coming into fishing docks are often unpaved and in deplorable condition with low maintenance due to county budget cuts (Njiru et al. 2008). The rehabilitation of the road and rail networks and/or fishing docks and ports could reduce travel times to and from the fishing docks.

A recent 2019 environmental and social impact assessment (ESIA) study report indicates that the revitalization of Kisumu Port could substantially improve fish catch and exports, and the sustainability of the fishing industry on the Winam Gulf (Ongore et al. 2018). Access to fishing docks is limited by the poor road network and the spread of hyacinth carpeting the water, which incapacitates boat movement and the poor state of fishing docks. The revitalization works include the removal of hyacinth and macrophytes on the Lake, maintenance of slipways, removal of the wreck to clear an area for shipbuilding and repairs, rehabilitating warehouses facilities such as cold storage for small scale fish traders arriving by the Lake, and maintenance of dry docks and hydraulic systems (Klemick et al. 2018).

Commercial fishing often happens early in the morning due to increased fish stock as sun rays hit the water surface (Orina, Onyango, Lungayia, Adrew Oduor, et al. 2020). This suggests that fish stock is a function of access to fishing docks. It is also a function of water hyacinth, which hinders water and land accessibility that negatively affects fish catch. Although commercial fishing may embody a direct use-value to consumers because of the relationship between fish supply and fish prices, the nonmarket lake attributes allow for an indirect use-value to nearby (proximal) property owners. HPM can be used to investigate this indirect use-value of fishing access through variation in residential prices and rents.

Designing a single statistical system for lake fisheries on Winam Gulf is challenging due to the Lake's characteristics. The Winam Gulf is characterized by multiple fish and fisheries stock, full and part-time and subsistence fishermen, human settlement along the meandering shoreline, variation in the setting of gear, the landing of catches in time and space and fishing skills, and multiple types and size of fishing gears and vessels (Kenya Ports Authority 2019). However, some studies have estimated fish catch using scientific and fish catch assessments (Ibrahim and Ramzy 2013; Jiwyam 2014). Fish species' spatial distribution shows that the *Lates niloticus* (Nile perch) is distributed in all fish docks and is the most dominant fish, followed by *Oreochromus niloticus* (Nile Tilapia). The main fishing gears in many fishing docks include boat seines, gillnets, longlines, beach seines, and paddled boats.

2.4 Developing Countries

HPM is widely used in nonmarket valuation research, especially for air and water quality in developed countries. Such HPM research applications are extensive on water quality impacts on recreational activities such as fishing, hunting, and snowboarding (Nicholls and Crompton 2017; Sander and Haight 2012). However, there is limited research on these water resource values in developing countries and commercial fishing. Since the sub-Saharan African region has been understudied for nonmarket valuation, little literature accounts for the real estate market in this region. Housing structural characteristics here differ from those in developed countries. There may be a need to account for the type of walls, roof, toilet, slum (commonly referred to as shanty) versus non-slum region, ancestral versus private land, availability of land ownership document, among other house price determinants. The inadequate study in this region is primarily due to these informal characteristics alongside low data access (Njiru et al. 2008).

Available data from a 2012/13 housing survey in Kenya provides an opportunity to use the HPM in sub-Saharan Africa. However, it is crucial to ensure that subjective perceptions from the respondent's description match objective measures in environmental valuation. Broadbent, Grandy, and Berrens (2010) showed that contingent valuation for valuing ecological goods might have persistent hypothetical bias. In this study, our specification may need to account for water pollution tolerance among households in the data from the fishermen's and house buyer's lens. This implies using access to fishing as the primary objective measure alongside water quality. In Artell, Ahtaiainen, and Pouta's

(2013) analysis on subjective and objective criteria in the valuation of water quality, the divergence of water quality perception may create bias. They use probit and multinomial logit models to explain this divergence in water quality perception for summer house owners. Artell, Ahtiainen, and Pouta (2013) decompose valuation with respect to the respondent, the house, and the water body. Their findings emphasize the need to account for individual perceptions, mainly when environmental quality in the study area differs from average quality.

3. DATA SUMMARY

3.1 Data Source

This analysis uses household-level cross-sectional data from the 2012/13 Kenya National Housing Survey (KNHS). Although a subsequent survey was conducted in 2015/2016, it lacks sub-location level household information, which is essential to estimate the distance from Lake Victoria. The 2012/13 KNHS sample includes information from completed questionnaires of renters and owner-occupiers alongside home builders, housing regulators, housing professionals, and housing financiers. The survey on renters and owner-occupiers uses a household-based sampling frame to generate a representative sample of households drawn from urban and rural areas. Each sub-location has 96,000 census enumeration areas from the 2009 Kenya population and housing census in this sampling method. It implements a multi-tiered structure of 4 sub-samples stratified based on county and further on rural and urban areas. Each sub-sample has 1340 clusters which have two-stage cluster sampling. Households have different weights.

3.2 Sample

The survey comprised household interviews of 12,150 house owner-occupiers and 19,826 renters. However, this analysis focuses on residential properties close to Lake Victoria on the Winam Gulf. Therefore, the research includes only households from 6 counties comprising approximately 135 geographic sublocations. This sorting represents 1,551 owner-occupier households and renters, which decreases to 1,301 due to data cleaning. A sub-location in Kenya has about 500 – 1100 households, which contains about 2,000 – 4,500 people. The survey used an in-person paper and pencil interview format facilitated by trained enumerators.

3.3 Proximity to the Fishing Docks, Hedonics and Summary Statistics

Given the underlying hypothesis that the value of a house incorporates the residual value from proximity to a fishing access point, it is essential to investigate distance as a determining variable. Analysis using ArcGIS software estimates the distance from the center of each sub-location to the nearest central fishing access point in kilometers (DOCKDIST). The data uses Kenya shillings currency converted to US dollars for analysis at the 2020 rate of 1 US dollar for 100 Kenya shillings.

This study uses self-reported monthly rent (RENT) and house sales value (HP20) to account for housing prices. Owner-occupiers reported the amount of money spent building their house. Further, loan information was obtained from the lenders for verification to reduce hypothetical bias from overreporting. The interviews included questions on the theoretical purchase and rent value that the occupier would charge and the actual values levied. Similarly, respondents reported on their reasons for buying or renting at their current location. Table 1 represents the owner-occupier house information.

The house structural characteristics (S) include the number of years in 2020 since the house was built (AGE), the type of house (BUNGALOW, FLAT, MAISONNETTE, SWAHILI, SHANTY, and TRADITIONAL), the land category (FREEHOLD, LEASEHOLD, GOVERNMENT, ANCESTRAL, COMMUNITY and UNSPECIFIED), the floor area measured in meters squared (in 10 meters squared increments), availability of verifiable house ownership documents (TITLE). For the type of house, bungalows, flats, and maisonnettes are expensive and often luxurious in characteristics, while traditional houses contain inexpensive building materials. Swahili houses are built with artistic methods and bear unique qualities, while shanty houses are affordable and stand in or near slums. Column 3 in table 1 denotes anticipated effects.

Table 1: Variable Names and Descriptions

Variable	Description	Anticipated Effect
Dependent Variables		
HP20	The selling price of the house, 2013 dollars	
RENT	Monthly rental payment, 2013 dollars	
Environmental Quality Characteristics (E)		
DOCKDIST	Distance to the nearest fishing dock (in kilometers)	Negative
WQI	Water quality index	Positive
House Structural Characteristics (S)		
FREEHOLD	Individually owned land 0= "no" 1= "yes"	Positive
LEASEHOLD	land under leasehold status 0 = "no" 1 = "yes"	Negative
GOVERNMENT	land government owned 0 = "no" 1 = "yes"	Positive
COMMUNITY	land community owed 0 = "no" 1 = "yes"	Negative
ANCESTRAL	land ancestrally owned 0 = "no" 1 = "yes"	Positive
BUNGALOW	Type of house if bungalow 0= "no" 1= "yes"	Positive
SWAHILI	Type of house if Swahili 0= "no" 1= "yes"	Positive
TRADITIONAL	Type of house if Traditional 0= "no" 1= "yes"	Negative
SHANTY	Type of house if Shanty 0= "no" 1= "yes"	Negative
FLAT	Type of house if Flat 0= "no" 1= "yes"	Negative

AGE	Number of years since house construction was completed	Negative
AGESQ	Square of the age of the house	Negative
TITLE	Availability of ownership proof 0= "no" 1= "yes"	Positive
House's floor size in square meters (SQM)		
BELOW10SQM	House's floor size below 10 square meters	Negative
SQM10_20	House's floor size between 10 to 20 square meters	Negative
SQM21_30	House's floor size between 21 to 30 square meters	Negative
SQM31_40	House's floor size between 31 to 40 square meters	Negative
SQM41_50	House's floor size between 41 to 50 square meters	Positive
SQM51_60	House's floor size between 51 to 60 square meters	Positive
ABOVE60SQM	House's floor size above 60 square meters	Positive
ROOMS	Number of bedrooms	Positive
Neighborhood Characteristics (N)		
RESIDENTIAL	Neighborhood house setup 0= "estate", 1= "residential area"	Positive
RURAL	Neighborhood development 0= "rural", 1= "peri-urban"	Positive
INC	Neighborhood level of income 0= "low" 1= "high"	Positive
SECURITY	Neighborhood level of security 0= "low" 1= "high"	Positive
VIHIGA	House is in Vihiga County	Negative
MIGORI	House is in Migori County	Negative
KISUMU	House is in Kisumu County	Positive
Social Institution (SI)		
ASSOCHERE	There is a neighborhood association 0= "false" 1= "true"	Positive

For the neighborhood component (N), the KNHS data includes a question on whether a household is a member of a neighborhood association, which will also represent a social institution component. This means that the neighborhood has a social system where individuals organize neighborhood activities (ASSOC). Houses were classified by income level, enabling a high- and low-income categorization to describe neighborhood income (INC). The Kenyan real estate market segments the housing market into "ESTATE and RESIDENTIAL." Estate is a community-styled house layout with adjacent properties closely knit together, while residential includes stand-alone houses further from neighboring homes. The neighborhood characteristic classifies (URBAN and PERI-URBAN). Peri-urban consists of an area immediately adjacent to a town. Respondents also self-reported their security perception (SECURITY). Table 2 presents the descriptive statistics of dependent and independent variables used in this study.

Table 2: Descriptive Statistics

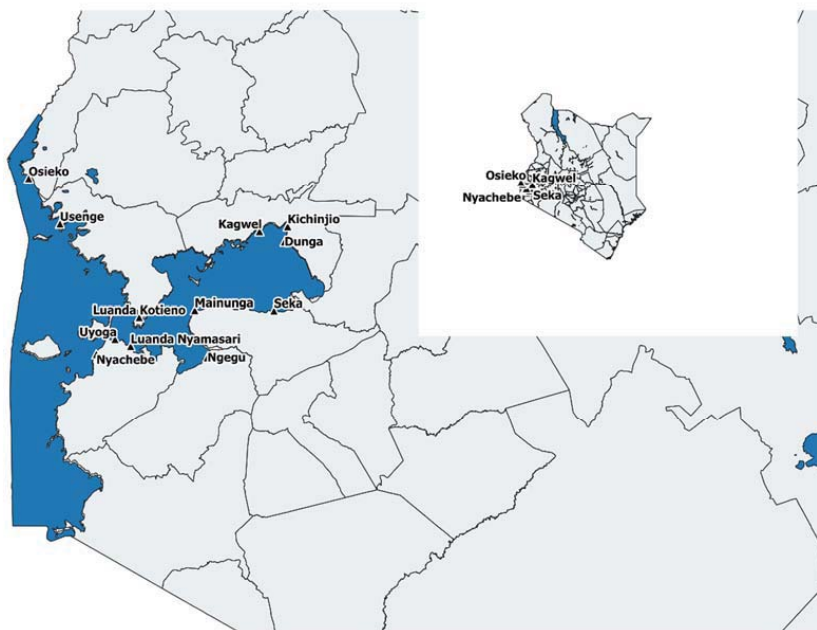
Variable	Obs	Mean	Std. Dev.	Min	Max
HP20	1301	86703.782	305487.87	200	5800000
RENT	1268	2425.972	8198.406	0	200000
DOCKDIST	1301	29.924	25.038	1.712	105.175
WQI	1301	35.983	4.39	27	44
FREEHOLD	1301	.44	.497	0	1
BUNGALOW	1301	.625	.484	0	1
SWAHILI	1301	.045	.208	0	1
TRADITIONAL	1301	.318	.466	0	1
SHANTY	1301	.008	.087	0	1
FLAT	1301	.004	.062	0	1
AGE	1301	18.903	10.31	7	74
AGESQ	1301	463.549	584.042	49	5476
BELOW10SQM	1301	.031	.173	0	1
SQM10_20	1301	.191	.393	0	1
SQM21_30	1301	.205	.404	0	1
SQM31_40	1301	.135	.342	0	1
SQM41_50	1301	.148	.355	0	1
SQM51_60	1301	.038	.19	0	1
ABOVE60SQM	1301	.253	.435	0	1
ROOMS	1301	2.3	1.203	1	6
TITLE	1301	.609	.488	0	1
RESIDENTIAL	1301	.984	.126	0	1
RURAL	1301	.681	.466	0	1
INC	1301	.549	.498	0	1
SECURITY	1301	.773	.419	0	1
NOASSOC	1301	.599	.49	0	1
ASSOCELSEWHERE	1301	.016	.126	0	1
ASSOCHERE	1301	.385	.487	0	1
VIHIGA	1301	.229	.42	0	1
MIGORI	1301	.14	.347	0	1
KISUMU	1301	.239	.427	0	1

3.4 Water Quality and Fishing Docks

Fishing is the main occupation for residents living within Lake Victoria counties. Fishers access the Lake primarily through twelve main beaches/ fishing docks: Nyachebe, Uyoga, Luanda Nyamasari,

Ngegu, Mainunga, Seka, Dunga, Kichinjio, Kawel, Luanda Kotieno, Usenge, and Osieko (see Figure 1). A recent study by Orina, Onyango, Lungayia, Andrew Oduor, et al. (2020) samples the water quality of 12 fishing docks at the Winam Gulf. Samples are from 6 fishing docks in September 2015 and 6 fishing docks in November 2015. These samples were subjected to spectrophotometric methods of Ammonium-Nitrogen ($\text{NH}_4\text{-N}$) and phosphate-phosphorus ($\text{PO}_4\text{-P}$).

Figure 1: Map of the Fishing Docks on Lake Victoria



Note: Author's compilation using QGIS

The water quality index (WQI) is based on nine parameters recommended by scientific studies and calculated using the water quality weight arithmetic index method (Shivanna and Nagendrappa 2015:191).⁵ These parameters include total dissolved solids (TDS), pH units (PH), total suspended solids (TSS), conductivity (COND), turbidity (TURB), temperature (TEMP), biochemical oxygen demand (BOD), Secchi disc (SECC) and dissolved solids (DO) from the sampled fishing docks. This study calculates the WQI based on the arithmetic weights of parameters suitable for the *Nile perch* and

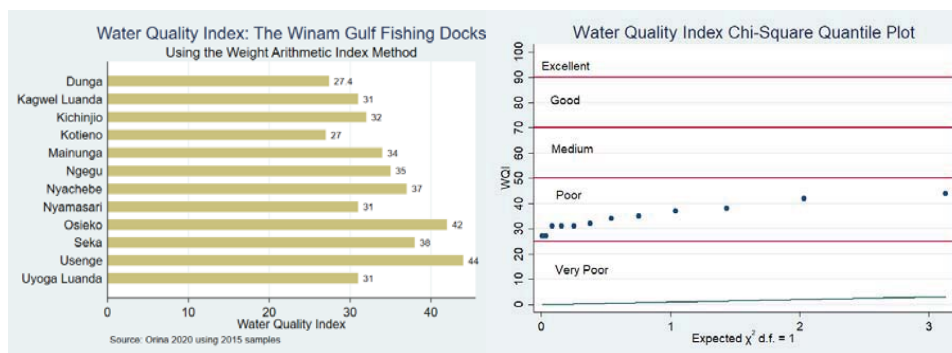
⁵ The water quality index is calculated based on Shivanna and Nagendrappa (2015); they use four step estimations of the weight arithmetic index method.

tilapia species, the most common fish in the Winam Gulf (Geheb et al. 2007; Taabu-Munyaho et al. 2016). For instance, the WQI suitable for *tilapia* includes total dissolvable solids ranging 127-137 mg/L, conductivity between 200 -235 $\mu\text{S/cm}$, *tilapia* is highly tolerant of low biochemical oxygen concentrations 4-6 mg/L, temperatures between 25.9-29.5 $^{\circ}\text{C}$, pH between 6.9-7.6, total suspended solid levels of below 280 mg/L, and dissolvable oxygen levels of 6-8 mg/L (Hernández et al. 2014; Jiwyam 2014). Similarly, for the *Nile perch*, suitable conditions include total dissolvable solids ranging between 50-100 mg/L, conductivity between 150-500 $\mu\text{S/cm}$, pH between 6.5-8, temperatures between 27.5- 38 $^{\circ}\text{C}$, and turbidity between 20.5-517 NTU (Ibrahim and Ramzy 2013; Kitchell et al. 1997).

$$WQI = f\{TDS, COND, BOD, TEMP, TURB, PH, TSS, SECC, DO\} \quad (1)$$

The weights from the water quality weight arithmetic index included 0.07 for TDS, 0.12 for COND, 0.11 for BOD, 0.10 for TEMP, 0.08 for TURB, 0.11 for PH, 0.12 for TSS, 0.12 for SECC, and 0.17 for DO. The overall WQI is compared with a given National Sanitation Water Quality Index range (NSWQI) of 0 –25 of very poor, 26-50 poor, 51-70 medium, 71-90 good, and 91-100 excellent. Given these metrics, all 12 fishing docks in this analysis have a water quality index in the poor range (27-44), as shown in Graph 1. The chi-square quantile plot illustrates the low variation in the water quality index using one degree of freedom. All fishing docks have a water quality index that is under the poor category. The chi-square quantile plot is used for data with a chi-squared distribution to often check for outliers and normality.

Graph 1: Water Quality Index at the 12 Fishing Docks on the Winam Gulf



Note: Author's compilation using calculated water quality index

This data has two main limitations. First, it only accounts for large fishing docks. This discounts cases where some households live near or can access smaller fishing docks. Second, it has insufficient access to roads, hospitals, markets, and government facilities apart from the rural/ urban dummy variable. House buyers may prefer houses near a paved road, a church, their workplace, or close to family and friends. The empirical model controls for houses in Kisumu town, which is more developed

than the other counties, to solve this problem partially. Similarly, homes in Migori and Vihiga counties are added to the model to reduce county fixed effects.

4. EMPIRICAL MODEL

Houses are heterogeneous goods. Assuming that the choice of housing is a composite good, that buyers maximize their utility, have limited income, and decide a house's location based on its characteristics, based on Rosen's model, these buyers' maximization problem takes the form as shown in equation 2.⁶

$$\max_{X,Z} U = f(X, Z, E) \text{ subject to } X + p(Z, E) = Y \quad (2)$$

Where U is the consumer's utility, X is the vector of other goods, Z is the one house that the consumer chooses, E is the environmental characteristics around the house's location, and Y is the consumer's income. To maintain a certain utility level ($\tilde{U}$) where $\tilde{U} = (X, Z, E)$, the price of Z that a consumer budgets for will be $\Omega = Y - X$. The consumer's problem becomes as equation 3:

$$\tilde{U} = U(Y - \Omega, Z, E) \quad (3)$$

Where Ω is the bid function that shows the maximum price level the consumer is willing to pay as a function of their target utility, income, and house characteristics, as in equation 4.

$$\Omega = (Y, Z, E, \tilde{U}) \quad (4)$$

The maximization of equation 2 has a first-order condition showing the marginal rate of substitution between characteristics of E and the consumption of X, which equals the price of E over the price of X (equation 5). Where $U_E(Z, E, X)$ is the partial derivative of U with respect to E and $U_X(Z, E, X)$ the partial derivative of U with respect to X. Price of E $\{P_E(Z, E)\}$, shows the marginal change in E. Therefore, the marginal implicit price is derived as equation 6.

$$\frac{U_E(Z, E, X)}{U_X(Z, E, X)} = P_E(Z, E) \quad (5)$$

$$P_E = \frac{\partial P_E(Z, E)}{\partial E} \quad (6)$$

This analysis decomposes house characteristics Z into the house structural characteristics (S), neighborhood characteristics (N), social institution characteristics (SI), and environment quality characteristics comprising of water quality (WQ) characteristics at the nearest fishing dock and the distance to the nearest fishing dock (D).

⁶ Rosen (1994) shows that when the indifference curve of a utility-maximizing individual is tangent to the HPM function she chooses among differentiated products that satisfy the first order optimization condition.

Applying the hedonic price model must account for functional form. This choice varies by case study area selected and by the underlying problem. Different studies have used various functional forms, including linear, semi-logarithmic, double logarithmic, Box-Cox transformation, and reciprocal (Chen 2017). Econometrics using flexible Box-Cox transformation shows that the log-linear method is the ideal transformation for this study. The log-linear method is widely used empirically due to its statistical performance, especially in mitigating heteroscedasticity issues.

The logarithm of house sales prices (equation 7 a & b), and house rental prices functional form (equation 8 a & b) was also the ideal fit for the sample given the AIC, normality of residuals, and the R-squared goodness of fit measure. Therefore, a hedonic price model may apply using the following log-linear specification.

$$\ln (HP20) = f \{S_{is}, N_{is}, SI_{is}, WQ_{is}, D_{is}\} \quad (7a)$$

$$\ln (HP20) = \beta_0 + \beta_D D_{is} + \beta_{WQ} WQ_{is} + \beta_N N_{is} + \beta_{SI} SI_{is} + \beta_S S_{is} + \varepsilon_{is} \quad (7b)$$

$$\ln (HR) = f \{S_{is}, N_{is}, SI_{is}, WQ_{is}, D_{is}\} \quad (8a)$$

$$\ln (HR) = \beta_0 + \beta_D D_{is} + \beta_{WQ} WQ_{is} + \beta_N N_{is} + \beta_{SI} SI_{is} + \beta_S S_{is} + \varepsilon_{is} \quad (8b)$$

Where β_0 , β_{FD} , β_{WQ} , β_N , β_{SI} , and β_S , are conformable coefficient vectors of S, N, SI, WQ, and D, respectively, while i represents a house and s a sublocation. Equation 7's dependent variable is the log of house sale prices, while equation 8's dependent variable is the log of annual rental prices. Similarly, equation 8 excludes the variable TITLE, which denotes the availability of house ownership proof.

4.1 Hypotheses

. Given the above log-linear specification, against a null hypothesis of no effect between distance to fishing docks and house prices (or rents), our alternate hypothesis that there is an effect between distance to fishing docks and house prices is as follows:

$$H_0: \beta_{FD} = 0 \text{ and } H_1: \beta_{FD} \neq 0$$

More specifically, we expect an increase in distance to the fishing docks decreases house price values ($\beta_{FD} < 0$), with implications that improved access to the nearest central fishing dock increases nonmarket values. Therefore, access to fishing docks should increase house prices and rental prices.

This analysis also focuses on water quality (WQ) at the nearest fishing dock and its effect on house prices. Again, against the null of no effect, the alternative hypothesis is that poor water quality will have a lower impact on house prices as the test involves:

$$H_0: \beta_{WQ} = 0 \text{ and } H_2: \beta_{WQ} \neq 0$$

5. EMPIRICAL RESULTS

Table 3 shows the estimated coefficients of the log-linear hedonic price model. Models 1 and 2 are trimmed models and provide evidence of robust coefficient before additional controls since signs remain unchanged. Models 3 and 4 are more extended and based on equations 7b and 8b, including house characteristics. Regressions cluster standard errors are at the Sublocation level to account for differences between households in different Sublocations in the cross-sectional sample and account for the fishing dock distance variable, which is at the sublocation level of data collection. The extended models, Models 3 and 4 in Table 3, had the lowest AIC of the regressions at 729.95 for owners and 776.81 for renters, and the highest R-squared at 64.7% for owners and 43.2% for renters. Therefore, model 3 is our preferred specification.

Results show that for every kilometer away from the fishing docks, house prices decrease by 1.37% while rental prices decrease by 1.93% at the 99% level of significance.⁷ Therefore, considering the mean value of house prices in this sample of \$86,703.78⁸, the average marginal implicit price of the access to fishing docks is \$1,187 (\$2013) or \$1804.24 (\$2020)⁹ per kilometer for house owners. Similarly, this access's average marginal implicit annual rent price is \$561.85 (\$Yr2013) or \$854 (\$Yr2020)¹⁰ per kilometer for renters. Where \$2,425.97 is the average monthly rent in the sample. All values were converted to US dollars using the 2020 conversion rate of Kenya Shillings (Kshs.) 99.98 for United States dollars (US\$) 1. Accounting for the annual periodicity of rental payments, on aggregate, renters have a significantly higher marginal implicit price per kilometer overall compared to owner-occupiers. Water quality is not statistically significant. These results led to the rejection of the null hypothesis that beta one equals zero.

Table 3: Ordinary least squares regression of the log of house price and log of rental prices

VARIABLES	(1) Log of House Sale Price	(2) Log of Monthly Rental Price	(3) Log of House Sale Price	(4) Log of Monthly Rental Price
DOCKDIST	-0.00581** (0.00255)	-0.00594*** (0.00156)	-0.0137*** (0.00402)	-0.0193*** (0.00495)
WQI	-0.00239 (0.0145)	0.0154 (0.0142)	0.000701 (0.0152)	-0.0103 (0.0163)
AGE			0.0480** (0.0188)	0.0488** (0.0221)
AGESQ			-0.00101*** (0.000227)	-0.000740* (0.000377)
ROOMS			0.113	0.368***

⁷ See Appendix B for log-linear calculations and interpretation.

⁸ Table 2 mean of HP20 dollar values in 2013

⁹ Calculated at the Kenyan inflation rate 1.52% during this period (i.e., \$86,703.78* 1.37 %). [Inflation rates in Kenya \(worlddata.info\)](#).

¹⁰ Calculated at the Kenyan inflation rate of 1.52% during this period (i.e., \$(2425.97*12) * 1.93%)

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			(0.127)	(0.0782)
TITLE			-0.464**	
			(0.204)	
RESIDENTIAL			-0.771***	-0.527
			(0.212)	(0.354)
RURAL			-0.0606	-0.169
			(0.170)	(0.177)
INC			-0.139	-0.0750
			(0.202)	(0.188)
SECURITY			0.110	0.152
			(0.167)	(0.179)
VIHIGA			-0.580	-0.487
			(0.358)	(0.362)
MIGORI			1.508***	1.168***
			(0.377)	(0.444)
KISUMU			0.509***	-0.286
			(0.170)	(0.210)
LEASEHOLD			-0.596	-0.652
			(0.496)	(0.486)
GOVERNMENT			3.083***	-5.637***
			(0.362)	(1.159)
COMMUNITY			-0.0861	0.406
			(0.276)	(0.344)
ANCESTRAL			-0.422**	0.119
			(0.185)	(0.159)
UNSPECIFIED			-0.164	0.328
			(0.576)	(0.526)
SWAHILI			2.080***	0.940*
			(0.600)	(0.515)
TRADITIONAL			-2.996***	-0.0279
			(0.431)	(0.800)
SHANTY			-1.409***	-0.735***
			(0.275)	(0.183)
SQMTR			0.273***	0.0810
			(0.0554)	(0.0496)
UTILITY			0.000189***	3.04e-05
			(4.60e-05)	(5.40e-05)
ASSOC			-0.178**	-0.0125
			(0.0708)	(0.0738)
Constant	10.45***	6.596***	10.63***	7.125***
	(0.506)	(0.526)	(0.699)	(0.804)
Observations	1,301	1,267	260	257
R-squared	0.015	0.028	0.647	0.432
AIC	4465.772	3779.912	729.9512	776.8179

Where: *** p<0.01 ** | p< 0.05 | * p< 0.1

Structural characteristics include the age of a house, which is associated with a higher house value of 4.8% per year for buyers and renters. The number of bedrooms is associated with a 36.8% higher rental price per bedroom increment but is insignificant for house sale prices. Similarly, square meters are positively associated with house prices by 27.3% per 10 square meters increment but insignificant for rental prices. The variable "Title" is the availability of ownership documentation which is negatively associated with house prices by 46.4% compared to unavailable titles. Compared to

houses not on government land, houses on government land are positively associated with 308% of house sale prices but are negatively associated with 563.7% of rental prices.

Houses on ancestral land are negatively associated with house sale prices by 42.2% compared to those not on ancestral land but are insignificant for rental prices. Swahili houses are positively associated with house prices by 208% at a 99% level of significance compared to non-Swahili make houses and associated with rental prices by 94% at a 90% level of significance. Compared to other houses, the traditional house is negatively associated with prices at 299% but insignificant for rental prices. Compared to non-shanty houses, shanty houses are negatively associated with rental and house prices at 140.9% and 73.5%, respectively. Utility payments are not an economically significant determinant of house price or rental rate.

For neighborhood characteristics, houses in the residential neighborhood are negatively associated with house prices by 77.1% compared to houses in the estate. Compared to houses in other counties, houses in Migori county were associated with higher house and rent prices of 150.8% and 116.8%, respectively. Compared to houses not in Kisumu County, houses in Kisumu County were associated with 50.9% higher house prices. Rural, income, and security variables were statistically insignificant. Being in a neighborhood association was associated with 17.8% higher house values but an insignificant effect on rent prices. This result confirms some studies' indication that social inclusion may increase land values.

6. DISCUSSION

The econometric results allow for the rejection of the first null hypothesis (H_0) that there is no relationship between distance to fishing docks and house sale prices. The evidence supports the alternate hypothesis (H_1), suggesting that proximal access to fishing docks is significantly and positively capitalized into the house prices around the Winam Gulf on the Kenyan side of Lake Victoria. House proximity to a fishing lake matters for owner-occupiers, as found in Calderón-Arrieta, Caudill, and Mixon (2019). As home buyers shop for houses, high demand for houses near the fishing docks is likely responsible for increased sales quotes around these regions. Investigating the underlying research questions helps determine whether communities in the lake region value living close to the Lake and, therefore, infer an underlying implicit willingness to pay extra for access to the fishing docks.

Apart from showing the implicit value of access to fishing docks, an additional contribution of this research is on the variation of this value between renters and house owner-occupiers. The marginal effect of distance to fishing docks on price is higher for rental prices than for owner-occupier prices. Unlike rental prices, house sale prices include a capitalized present value. For comparison, assuming

a five-year stream of future annual rent and a 5% discount rate, the renters have a higher marginal implicit price than owner-occupiers by 34%.¹¹¹²

The net benefits from improving access to fishing docks by renovating/ revitalizing docking stations, building additional ports, initiating environmental sustainability programs on the Lake, and enhancing infrastructure for fishers are likely to increase welfare for communities around Lake Victoria. The marginal implicit value of 1.37% of the average house sales price per kilometer for owner-occupiers and 1.93% of annual average house rent per kilometer for renters offers a significant value proposition for these improvements. The marginal implicit value is higher for renters than for owner-occupiers, possibly due to the high demand for rentals than house purchases due to capital limitations, as in most developing countries.

The analysis fails to reject the null of no effect for the alternative hypothesis (H_2) that water quality at the fishing docks positively affects house sale prices and rental prices because the estimated coefficient β_{WQ} is not statistically different from zero. These results are not consistent with existing literature that support the positive relationship between water quality and house prices (e.g., Papenfus 2019; Klemick et al. 2018). Several possibilities could explain these contradictory results, alone or in combination, about the real estate consumers' water quality awareness and the lack of water quality variation at the study region's lakefront properties. As shown in Graph 1, the WQI from the 12 fishing docks ranges from the lowest at 27 to the highest at 44.

First, it may be that owner-occupiers and renters on properties near the Lake are likely unable to distinguish water quality levels between different fishing docks because of the scientific nature of these measurements that are not often accessible. Similarly, the relationship between water quality and real estate through the fish catch, morbidity rates linked to malaria and other waterborne diseases, and access to other social amenities might influence buyers' accurate water quality estimation.

Perhaps most importantly, the National Sanitation Water Quality Index range (NSWQI) places the water quality in the 12 fishing docks used in this study under the "poor" range category. Having all fishing docks under one low-quality umbrella or range likely does not offer enough variation to infer the effect of water quality on house prices or rent. For example, absent spatial variation in our data across the 12 sites, it may be that a before-and-after research design (e.g., with panel data on housing prices and rents and given treatments) will be needed to thoroughly investigate the economic effects of treating hyacinth around these fishing docks. Thus, we caution that our results should not be interpreted

¹¹ The average marginal implicit price for owner occupiers is \$1804.24 per kilometer, and for renters' is \$854 per kilometer.

¹² Average house sales (which turn over every five years on average) have a capitalized present value of \$1804.24; this can be compared to a present value of five-year rental annuities of \$563.65, with a discount rate of 5%, which equal \$2440.31

that water hyacinth problems in the region are not affecting fishing and water quality; instead, it is just that we do not see such effects in our cross-sectional sample of house prices and rents.

Given these results, improving access to fishing docks has substantial implications on the welfare of house owner-occupiers and renters in this region. These results imply that improving the road network, renovating fishing docks increase lakefront properties' values. It also establishes a mechanism for enhancing the community's welfare because of the indirect relationship between increasing fishing docks' infrastructure on food security through an increased fish catch. This study does not imply that it does not affect lake property on Winam Gulf for water quality. It may be that the lack of variation of water quality in the fishing docks fails to allow for the estimation of this relationship.

7. CONCLUSIONS

Economic evidence on monetary values for proximity/access to fishing docks can provide essential inputs to assessing various public projects, including revitalization projects on road networks and conservancy projects under consideration for communities living near Lake Victoria. Developing countries need to accelerate the transformation of such projects to initiate creative development (Patlasov and Zharov 2017). This study uses the hedonic pricing method (HPM) to estimate the marginal implicit value of access to fishing docks in the Winam Gulf on Lake Victoria in Kenya. There is limited research in sub-Saharan Africa due to data-related challenges and unique house designs. Similarly, there is little research on lake valuation related to indirect use-values for access to commercial fishing. Researchers explore the total economic value for lake resources and use different nonmarket valuation techniques to value indirect use-values. We also investigate the potential effects of a recently available water quality measure. This study combines 2012/13 survey data from the Kenya National Bureau of Statistics, ArcGIS spatial information, and water quality data from 12 fishing docks (Orina, Onyango, Lungayia, Andrew Oduor, et al. 2020). The water quality index is constructed using a weighted arithmetic index method based on nine water quality parameters.

Econometrically, hedonic price regression decomposes observed variation in house price (or rent) into the effects of various housing attributes, including structural characteristics, spatial characteristics (e.g., distance to fishing docks), and neighborhood and environmental characteristics. For example, one focal point here was on fishing access, where we map the distance to fishing docks using the 'near proximity' tool on ArcGIS software. Our expectation was that proximity (closeness) to fishing access would be positively valued (or inversely related to distance). Consistent with our hypothesis, results show that for every kilometer away from the fishing docks, house prices decrease by 1.37% while rental prices decrease by 1.93%. Therefore, considering the average house sale price in the sample, proximity to fishing docks positively affects property values by \$1804.24 per kilometer for house purchases and \$854 per kilometer for annual house rent. The former (\$1804.24 per km) represents the increment to the capitalized present value of proximity in a house sale, but the latter (\$854) is an annual rent increment. Our sample data would note that houses in the area turn over

relatively frequently (e.g., averaging every five years). However, even if the annual rent increment for our average house were paid out for, say, just five years and discounted back to the present value (at a 5% discount rate), it would represent \$2440.31. Thus, while the results support the hypotheses that both house buyers and renters are willing to spend more on houses for fishing access, renters are willing to pay significantly more in present valued terms.

Contrary to our expectation, econometric results show no evidence that a given measured water quality index (Orina, Onyango, Lungayia, Andrew Oduor, et al. 2020) significantly influences house sales or rental prices. Several propositions, separately or in combination, may explain the deviation of this result from the literature on water quality as a function of house prices. First, this information may not yet be widely available or discernible to consumers in the Kenyan housing market. Second, the lack of variation in the given measured water quality index (i.e., uniformly low or poor quality) may explain the lack of effect on house sales prices or rental prices.

In closing, in this developing country context, HPM results on estimated marginal implicit prices for various attributes, from house owners and renters, help us understand the total economic value generated by lakes. Such economic values can help inform policy considerations. For example, HPM results support improving access to fishing docks as a welfare improvement mechanism for communities living by the Lake on Winam Gulf. However, there is also clearly room for further understanding on water quality effects (e.g., water hyacinth), and we leave this to future research. We hope that this research spurs additional investigation.

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9. APPENDICES

A. Water Quality Index

WQI is based on the parameters suitable for the Nile perch and tilapia species, the most common fish in the Winam Gulf (Taabu-Munyaho et al. 2016).

$$WQI = f\{TDS, COND, BOD, TEMP, TURB, PH, TSS, DO\} \quad (1)$$

The water quality index is calculated based on Shivanna and Nagendrappa (2015) four-step estimations of the weighted arithmetic index method (available upon request from the lead author).

B. Log-linear Model Calculation

The specification in equation 7b presents the primary relationship between distance to fishing Docks (D) and house sale prices. Holding other factors constant, we are interested in the interpretation of coefficient β_D . We can first demonstrate that $\Delta \log(HP)$ is approximately equal to $\% \Delta(HP)$.

$$\begin{aligned}
 \Delta \log(\text{HP}) &= \log(\text{HP1}) - \log(\text{HP0}) \\
 &= \log(\text{HP1}/\text{HP0}) \\
 &= \log\left(\frac{\Delta \text{HP} + \text{HP0}}{\text{HP0}}\right) = \log\left(\frac{\Delta \text{HP}}{\text{HP0}} + 1\right) \\
 \sim \frac{\Delta \text{HP}}{\text{HP0}} &= \% \Delta(\text{HP})
 \end{aligned}$$

This approximation is based on a Taylor series expansion around x, where $\log(x+1)$ is approximately equal to x. Therefore, a change in D leads to roughly a percent change in HP of $100 * \Delta \beta_D$. This estimation is derived as follows:

$$\begin{aligned}
 \% \Delta(\text{HP}) &= \frac{\text{HP1} - \text{HP0}}{\text{HP0}} = \frac{\text{HP1}}{\text{HP0}} - 1 \\
 &= \exp(\log(\text{HP1}/\text{HP0})) - 1 \\
 &= \exp(\Delta \beta_D D_{is} + \Delta \varepsilon_{is}) - 1 \\
 &= \exp(\Delta \beta_D D_{is}) - 1 \text{ where } \Delta \varepsilon_{is} = 0
 \end{aligned}$$

Therefore, from equation 7b, to interpret this log-linear function, a unit increase in D multiplies the value of HP20 by $\exp(-0.0137) - 1$ since integrating the central equation is as follows:

$$\text{Ln}(\text{HP20}) = 10.63 - 0.0137D$$

$$\frac{\Delta \text{Ln}(\text{HP20})}{\text{HP20}} * 100 = -0.0137 * (\Delta D) * 100$$

Thus, a kilometer change in D is associated with a 1.37 percent in HP.