DISSERTATION

THREE ESSAYS ON DISEASE, DEVELOPMENT, AND INTERVENTION

Submitted by

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ABSTRACT

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The effect of health on development is well documented in the literature. Generally, variables like life expectancy and infant mortality are used as proxies for overall health. These variables encompass all potential causes of mortality and morbidity and may not provide useful policy prescriptions. Individual diseases are explored as well, such as malaria, but are not necessarily compared. This paper will map the income and age profile of 150+ individual causes of mortality. Mortality data are explored for 150+ causes, for 185 countries in 1990 and 2010. We summarize the data to show that mortality rates certain low income burdens decline rapidly as income grows while other remain constant, or even increase. We also develop a framework with with the individual relationships between burdens the income growth or vice-versa could be explored.

We present a multi-species dynamic population model of wildlife management in which a manager applies spatial or individual-based disease protection interventions to a wildlife species with high existence value. We use the model to investigate the choice between the alternative interventions assuming the manager's objective is to 1) maximize abundance subject to a budget constraint or 2) minimize management costs subject to a desired abundance level. The model is specifically used to analyze population dynamics between the endangered black footed ferret and prairie dogs which are susceptible to sylvatic plague outbreaks. While specific results are sensitive to biological and economic parameters, we find a defined switch point between the recommended use of spatial vs. individual disease mitigation interventions based on either a target population or potential fixed budget. Below a specific

budget or target abundance, individual-based protection should be used, while above, spatial protection should be used.

We present an individual-based stochastic simulation model of wildlife population and disease dynamics under different management strategies. Our objective is to estimate the cost and biological outcome of various vaccination strategies against rabies in Kwazulu-Natal, South Africa. A health economic data assessment such as we present here is a crucial component of disease control. This analysis can guide management decisions by highlighting cost-effective strategies. At a broader level, it will provide information to policy makers and other stakeholders regarding both the feasibility and public health benefits, stemming from reduced canine to human transmission, of the elimination of canine rabies.

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1.1. Introduction

Global disease and other causes of premature mortality accounted for an estimated 52.8 million deaths in 2010, many of them entirely preventable [1]. The reduction in disease related mortality and disability is an important objective from a social, as well as economic perspective. From a social perspective, health plays a crucial and direct role in the overall life expectancy, and the quality of life of an individual. In many cases, children and young adults are the primary victims of preventable disease, and contribute to the majority of deaths and disabilities [2]. It has been estimated that the value of gains in health are of the same order of magnitude as gains in income in terms of social welfare [3].

From an economic perspective, health has a more indirect influence through its contribution to human capital. Health influences the productivity of labor, the size of the labor force, and contributes to cognitive abilities. Much of the literature agrees that improving health can lead to large tangible payoffs by increasing economic growth. Disease eradication has been shown to lead to improved education, higher literacy rates, and long term personal income gains [4]. In terms of economic growth, [5] finds that higher mortality rates lead to shortened decision horizons yielding higher short-term benefits at the expense of long-term gains. It then follows that by extending the decision horizon through longer life expectancy, long term economic gains should follow. Further, improvements in health can also lead to higher rates of productivity among workers, and larger labor pools [6, 7]. While there is substantial cross-country regression evidence to support the idea that health (generally in terms of life expectancy or infant mortality) is indirectly correlated with improved economic growth and development, it is far from conclusive as to the causal relationship between the

two. It is, however, conclusive that health plays an important role in social welfare at the micro and macro levels.

This paper explores disease burden profile transitions and economic growth. We attempt to identify burdens with high marginal returns to investment, where initial and relatively small investments return large health gains. While aggregate measures of health have long been used in empirical estimations, they may not provide useful policy prescriptions. A particular conclusion may be that life expectancy is positively correlated with income per capita, though for policy makers, the implications may be less clear. The suggestion of increasing life expectancy to increase economic growth provides little guidance on how to accomplish the goal. There are a number of factors that influence life expectancy and that may vary significantly by country or income group. Rather than looking at overall life expectancy or infant mortality, which include all possible causes of mortality and disability, individual diseases and bundles of diseases are analyzed within different levels of development to identify how relevant disease profiles shift through development stages, and their relationship with income. By analyzing individual causes of mortality and morbidity, more specific and targeted policy prescriptions can be made. Data for 256 diseases and other causes of mortality and disability for 185 countries are used to analyze these movements and relationships. Data were obtained for the years 1990 and 2010.

Beyond aggregate health measures, individual diseases can and do have a large impact on overall well-being and economic development, and may provide a better explanation of income, growth, or development in certain locations. Malaria has long been shown to significantly depress potential growth in Africa and Asia. [8] conclude that eradicating malaria in subsaharan Africa will lead to a permanent increase in annual growth of 2.6%. [4]explores

the effect of hookworm eradication in the American South circa 1910. He concludes that the hookworm infection rate could directly account for roughly half of the literacy gap and 20 percent of income differences between the American North and South at the time.

While diseases like malaria and hookworm are geographically specific, and generally present primarily in low income countries, middle and high income countries face their own set of influential disease burdens. Obesity among high income countries is growing at a rapid pace. Obesity rates in the United States are projected to reach roughly 40 percent in men, and 43 percent in women by the year 2020 [9]. The financial burden on national budgets, business, health care providers, and individuals is well documented and substantial. In the United States alone, [10] find that in 1998, obesity accounted for between 1 and 8 percent of the national health expenditure, with the cost to business being reported to reach $12 billion per year [11]. Regarding wages, [12] find that obese workers suffer from wage penalties ranging from 0.7 to 6.3 percent relative to their non-obese counterparts. The aggregate size of national labor force is also impacted. [13] finds that obesity rates have a significant and negative impact on employment for both men and women. The marginal employment effect for obese men was found to be -0.084, while obese females have a probability of employment that is 0.213 lower than non-obese females.

Expected disease burdens vary significantly between low, middle, and high income countries. It is important then, to understand these shifts as a country moves from one development stage to the next. As household income rises in low income countries, individuals may be better able to invest in preventative care to avoid certain disease burdens such as malaria or tetanus. Diseases like malaria and tetanus, which are most common in low income countries, can be more easily avoided through the purchase of bed nets, or oral medication

for malaria, and simple injections for tetanus. From a public health perspective, increased income may also lead to increased tax funding for additional public health projects such as mass polio vaccination, etc. There may then be a distinction between causes of mortality and morbidity that are primarily dealt with by private individuals through insurance and health care and those causes that are addressed using state resources through public health projects. Movement through development stages will influence both private access to preventative care as well as the state's ability to combat certain burdens and provide better care. Better access to health care will undoubtedly increase life expectancy and improve well-being. While life expectancy has been shown to be positively correlated with economic growth [14], it may bring with it new causes of mortality and morbidity in the form of increased risk of cancers, cardiovascular diseases, etc.

Disease burden shifts can occur for many reasons: increased access to health care, rising income, longer life expectancy, etc. Diet for example, can change significantly as income increases, though not always for the better. [15] find that rapid income growth in China between 1989 and 1997 has led to a shift to more low quality foods with negative impacts on heath, with low-income groups experiencing the largest increase in detrimental effects. Cancer, on the other hand, is a disease of old age that is greatly affected by life style. Cancer detection and diagnosis normally occurs around the age of 50 or later in the United States [16]. Along with cancer, the risk of diseases like Alzheimer, arthritis, type 2 diabetes, and cardiovascular disease increases greatly with age.

This paper will analyze how disease burdens shift through development stages and economic growth. From a social planner's perspective, who is interested in maximizing the aggregate social welfare of a population, it is important to understand how growth may be

related the health of individuals as well as understanding the marginal benefit of health investment. Growth from a low to a middle income country might lead to fewer cases of malaria and tetanus, but increased cases of obesity and diabetes. Moving from a middle income country may lead to higher cases of cancer, and other diseases of old age. The ability to plan for such shifts, in the form of health care reforms, awareness campaigns, etc., could reduce the expected impact. Likewise, at each income group, there are likely burdens that should be focused on as smaller relative investments may yield larger returns. This paper contributes to the literature by going beyond the general aggregate measure of health, life expectancy or infant mortality, and exploring the relative impact of individual causes of mortality and morbidity on income and growth. Other non-disease causes of mortality and disability are also considered such as auto accidents and self harm.

1.2. Data

Crucial to this empirical analysis is the construction of cross-country mortality and disability rates for a wide range of potential diseases. Data for 229 causes of mortality and disability were obtained from the Global Health Data Exchange, which were collected by the Institute for Health Metrics and Evaluation for the 2010 Global Burden of Disease Study. Data are presented in the form of disability adjusted life years (DALY), deaths, years of life lost due to premature mortality (YLL), and years lived with disability (YLD). These measure are broken down further into aggregate values, rates per 100,000 population, and relative percentages within countries. For example, looking at DALYs for a specific country, the total number of DALYs for each cause is available, as well as the DALY rate per 100,000 population, and the relative percentage of total DALYs that each cause contributes.

Mortality related measures (deaths, and YLL) included only 182 of the total 229 causes as some causes do no cause mortality. Causes such as ADHD and Autism are sources of YLD, though they do not contribute to mortality.

Along with disease burden data, other cause of mortality and disability are also included in this data set. These causes include auto accidents and other road injuries, nutritional deficiencies, self harm, various forms of assault, mental disorders, and others. See Table A.1 for a full list of causes of mortality and disability. Data on GDP per capita were collected from the World Bank and are adjusted to $2005.

1.3. Disease Burden Transition

In order to illustrate the disease and cause burden shift through development stages, causes were ranked based on the expected income of afflicted individuals. Using deaths as an example, this was done using a weighted average GDP per capita using the following function

$$E[GDP_i] = \sum_{k=1}^{K} GDP_k \frac{Deaths_{i,k}}{\sum_{n=k}^{K} Deaths_{i,k}} \tag{1.1}$$

where $E[GDP]$ is the expected GDP per capita of an individual dying from cause, i. The denominator of equation 1.1 is the aggregate global deaths associated with cause i. The numerator is the summation of GDP per capita of country k, multiplied by the deaths from cause i in country k. This expression tells us the expected GDP per capita of individuals that die from each of the causes of interest, and allows us to rank causes by their expected income per capita. So then, causes with a lower GDP per capita would be interpreted as disproportionately affecting individuals in low income countries, and causes with higher GDP per capita would be interpreted as affecting individuals in high income countries. So then,

as a country moves from low to mid to high income, one could expect the expected disease or cause burden to follow this ranking. Table 1.1 lists the causes ranked based on mortality rates in 2010 from the lowed expected per capita income to the highest [1]. The standard deviation of the weighted income and the max probability density (discussed below)are also provided. If we look at the first cause on the list, Tetanus, we would expect the annual income of an individual who has died from Tetanus to be $878. The relatively large max density of distribution of incomes for this cause suggests that Tetanus mortality is primarily occurring in the lowest of income groups with mortality rates declining rapidly with income growth.

TABLE 1.1. Income Ranked Cause List With Expected Per Capita Income and Max Density. 2010

Cause	Expected Income	Standard Deviation	Max Density	Expected Age Group
Tetanus	878	9.43	0.361	0-14
Malaria	1,020	24.68	0.095	0-14
Obstructed labor	1,065	14.37	0.197	15-64
Maternal sepsis	1,358	18.15	0.324	15-64
Maternal hemorrhage	1,385	18.05	0.333	15-64
Abortion	1,456	18.71	0.359	15-64
Measles	1,499	27.53	0.239	0-14
Other: maternal disorders	1,514	18.35	0.455	15-64
Syphilis	1,516	28.31	0.346	0-14
Pneumococcal meningitis	1,546	12.33	0.479	0-14
Neonatal sepsis	1,550	10.84	0.385	0-14
Maternal hypertension	1,569	17.83	0.359	15-64
Glomerulonephritis	1,641	8.75	0.506	65+
HiB meningitis	1,646	27.35	0.468	0-14
Whooping cough	1,763	32.33	0.270	0-14
Acute hepatitis A	1,767	13.15	0.349	65+
Meningococcal	1,798	13.77	0.333	0-14

[1]The ranked burden table for 1990 can be found in the Appendix

Otitis media	1,902	6.50	0.747	0-14
Rabies	1,932	23.64	0.340	15-64
Other: neonatal disorders	1,962	19.11	0.393	0-14
Protein-energy malnutrition	2,009	21.70	0.363	65+
Meningitis	2,042	17.95	0.408	0-14
Diarrheal diseases	2,047	21.05	0.394	0-14
Tuberculosis	2,107	14.18	0.474	65+
Animal contact	2,169	16.49	0.457	0-14
Neonatal encephalopathy	2,272	15.17	0.490	0-14
Neonatal disorders	2,329	15.68	0.475	0-14
Nutritional deficiencies	2,332	21.14	0.302	65+
Diptheria	2,382	92.72	0.513	0-14
Typhoid fevers	2,491	25.74	0.258	15-64
Upper respiratory infections	2,492	31.81	0.316	65+
Encephalitis	2,550	18.46	0.354	0-14
Other: meningitis	2,772	22.62	0.360	0-14
HIV AIDS	2,904	47.57	0.244	15-64
Preterm birth complications	3,035	20.92	0.389	0-14
Mechanical forces (firearm)	3,247	35.85	0.302	15-64
Cleft lip and palate	3,256	31.14	0.336	0-14
Sickle cell	3,309	64.12	0.207	0-14
Neural tube defects	3,452	59.82	0.341	0-14
Acute hepatitis B	3,551	28.13	0.265	65+
Other: road injury	3,635	41.56	0.363	65+
Iron-deficiency anemia	3,695	31.33	0.198	65+
Other: infectious diseases	4,161	39.38	0.309	0-14
Appendicitis	4,366	34.74	0.275	65+
Assault by sharp object	4,425	36.74	0.271	15-64
Epilepsy	4,477	33.15	0.313	65+
Fire	4,572	30.55	0.292	65+
Other: NTD	4,572	50.70	0.278	0-14
Interpersonal violence	4,702	38.09	0.265	0-14
Iodine deficiency	4,742	45.18	0.219	65+
Assault by other means	4,759	30.86	0.246	0-14
Assault by firearm	4,933	65.21	0.233	15-64
Mechanical forces	5,242	42.42	0.225	15-64
Hemoglobinopathies	5,272	49.73	0.300	0-14
Poisonings	5,325	48.02	0.233	0-14

Other: STDs	5,427	45.42	0.248	65+
Pedestrian road injury	5,433	65.13	0.252	65+
Chlamydia	5,459	45.73	0.248	65+
Gonnorhea	5,462	45.80	0.248	65+
Drowning	5,465	39.75	0.266	15-64
Asthma	5,495	41.38	0.254	65+
Other: congenital anomalies	5,524	52.40	0.261	0-14
Congenital anomalies	5,929	48.28	0.260	0-14
Other: nutritional deficiencies	5,983	62.14	0.169	65+
Other: gynecological disorders	6,033	63.26	0.176	65+
Varicella	6,159	50.06	0.349	0-14
Gynecological diseases	6,309	65.45	0.174	65+
Bacterial skin diseases	6,373	61.09	0.292	65+
Thalassemia	6,471	70.15	0.268	0-14
Congenital heart anomalies	6,512	46.31	0.250	0-14
Cellulitis	6,524	61.29	0.300	65+
Fibroids	6,533	93.33	0.176	15-64
Other: hemog	6,662	59.77	0.248	0-14
Other: skin diseases	6,665	64.69	0.319	65+
Cervical cancer	6,685	46.08	0.217	65+
Acute hepatitis C	6,792	63.42	0.205	65+
Lower respiratory infections	6,796	66.34	0.319	0-14
SIDS	6,923	70.00	0.310	0-14
Other: mechanical forces	7,039	68.86	0.230	15-64
Other: transport injuries	7,134	57.28	0.224	15-64
2 Wheel road injury	7,152	58.46	0.210	15-64
Transport injuries	7,197	54.37	0.219	65+
Road injury	7,202	55.07	0.218	65+
Other: chromosomal anomalies	7,548	71.26	0.234	0-14
Other: unintentional injuries	7,828	77.96	0.254	0-14
Bicycle road injury	7,912	75.07	0.225	65+
Dengue	7,956	86.30	0.182	65+
Urolithiasis	8,052	68.01	0.235	65+
G6PD deficiency	8,142	63.46	0.229	65+
Unintentional injuries	8,283	73.30	0.249	65+
Peptic ulcer	8,404	84.54	0.259	65+
4 Wheel road injury	8,726	73.51	0.203	15-64
Hemorrhagic stroke	8,803	79.87	0.206	65+

Adverse medical treatment	8,821	91.46	0.248	0-14
Inguinal and femoral hernia	8,826	75.26	0.163	65+
Cirrhosis	8,874	78.59	0.221	65+
Rheumatic heart disease	8,956	83.73	0.244	65+
Diabetes	9,093	71.98	0.206	65+
Down's syndrome	9,126	90.80	0.220	0-14
Other: respiratory diseases	9,206	127.39	0.219	0-14
Other: urinary diseases	9,213	87.00	0.195	65+
Gastrititis and duodenitis	9,298	79.12	0.190	65+
Schizophrenia	10,000	112.10	0.242	65+
Intestinal obstructions	10,051	104.22	0.238	65+
Other: endocrine	10,085	102.00	0.161	0-14
Hodgkin's lymphoma	10,126	86.85	0.193	65+
Hypertensive heart disease	10,216	88.07	0.178	65+
Stroke	10,293	86.78	0.185	65+
Hypertensive CKD	10,355	81.16	0.205	65+
Liver cancer	10,357	104.18	0.203	65+
Pancreatitis	10,373	90.72	0.172	65+
Cardiomyopathy	10,474	106.24	0.170	65+
Diabetic CKD	10,511	97.86	0.216	65+
Endocarditis	10,546	93.61	0.203	65+
Digestive diseases	10,710	103.34	0.225	65+
Endometriosis	10,729	405.90	0.129	15-64
Decubitus ulcer	10,775	122.97	0.221	65+
Chronic kidney disease	10,845	90.53	0.231	65+
Other: digestive diseases	11,081	115.10	0.220	65+
Other: CKD	11,235	97.83	0.244	65+
Pneumoconiosis	11,280	144.91	0.250	65+
Other: neurological disorders	11,293	108.83	0.190	65+
Larynx cancer	11,432	100.16	0.154	65+
Rheumatoid arthritis	11,519	136.24	0.226	65+
Ischemic stroke	11,585	102.04	0.196	65+
Eating disorders	11,906	129.52	0.189	65+
Cardio and circulatory diseases	11,963	107.04	0.171	65+
Nasopharynx cancer	12,037	171.16	0.172	65+
Other: drug use	12,103	137.95	0.148	0-14
Testicular cancer	12,173	123.86	0.150	65+
Musculoskeletal disorders	12,269	125.72	0.180	65+

Stomach cancer	12,293	129.50	0.172	65+
Self harm	12,348	121.72	0.188	15-64
Chronic respiratory diseases	12,475	127.92	0.254	65+
Inflammatory bowel disease	12,525	146.04	0.247	65+
Other: musculoskeletal	12,558	127.72	0.157	65+
Ischemic heart disease	12,649	117.72	0.162	65+
Other: mental and behavioral	12,726	144.21	0.203	65+
Non-melanoma skin cancer	12,995	119.71	0.169	65+
Gall bladder diseases	13,178	130.42	0.192	65+
Esophageal cancer	13,247	142.25	0.175	65+
Urinary diseases	13,296	138.53	0.174	65+
Mental and behavioral disorders	13,340	147.87	0.156	65+
Other: cancers	13,393	137.82	0.235	65+
Alcohol use disorders	13,788	182.85	0.138	15-64
Genital prolapse	13,883	194.86	0.097	65+
Cocaine use	13,896	169.30	0.151	0-14
Mouth cancer	14,265	141.55	0.151	65+
Other: pharynx cancer	14,328	159.63	0.164	65+
COPD	14,440	158.31	0.207	65+
Thyroid cancer	14,464	141.21	0.170	65+
Opioid use	14,993	182.63	0.145	0-14
Amphetamine use	15,204	186.15	0.141	0-14
Other: cardio and circulatory	15,307	170.35	0.168	65+
Gallbladder cancer	15,522	175.95	0.151	65+
Pyelonephritis and UTI	15,777	172.20	0.160	65+
Falls	15,904	193.88	0.227	65+
Leukemia	16,237	167.98	0.208	65+
Uterine cancer	16,579	173.72	0.150	65+
Non-Hodgkin lymphoma	16,882	180.78	0.175	65+
Breast cancer	16,955	180.70	0.160	65+
Ovarian cancer	18,333	203.77	0.163	65+
Brain cancer	18,404	213.00	0.150	65+
Bladder cancer	18,696	207.00	0.139	65+
Prostate cancer	18,996	214.94	0.133	65+
Interstitial lung diseases	19,109	255.31	0.190	65+
Neurological disorders	19,258	252.12	0.214	65+
Lung cancer	19,386	212.20	0.138	65+
Vascular intestinal disorders	19,567	222.55	0.107	65+

Pancreatic cancer	19,992	220.01	0.128	65+
Colorectal cancer	20,040	218.83	0.144	65+
Melanoma	20,231	262.62	0.120	65+
Multiple sclerosis	20,402	268.59	0.157	65+
Kidney cancers	20,863	239.78	0.130	65+
Aortic aneurysm	20,879	254.84	0.142	65+
Peripheral vascular disease	22,388	284.52	0.133	65+
Myeloma	23,716	278.65	0.138	65+
Parkinson's disease	24,428	311.13	0.173	65+
Atrial fibrillation	25,352	351.45	0.118	65+
Alzheimer's disease	29,621	439.54	0.136	65+

Malaria on the other hand, has a low expected income but a low max density, suggesting that as income grows, mortality rates decline at a much slower rate. We would assume that Malaria mortality remains relatively high through multiple income groups.

Intuitively, causes on either extreme can be interpreted as being very GDP per capita specific, or that they disproportionately affect individuals on either the low or high income portion of the scale. The causes that fall in the middle are less clear as to who is primarily affected. It could be that the causes are specific to middle income individuals, or it could be that the causes span multiple income groups from low to high, and fall in the middle simply as an overall average. This would mean that certain causes may follow individuals with similar probabilities throughout several development stages. In order to evaluate whether causes are income specific or span multiple income groups, the standard deviation of weighted income of each cause is calculated. The standard deviation provides insight into the distribution of incomes associated with a specific cause. A large standard deviation indicates a cause that spans multiple income groups, while a small standard deviation indicates a tight distribution around a specific income.

It is also true, however, that we would expect the standard deviation to increase as the absolute value of expected income increases. This may lead to the spurious assumption that since the standard deviation of a high income cause is larger than a low income cause, that the high income cause spans more income groups than the low income cause. To appropriately compare the income distribution of each cause, a distribution was estimated. We would assume that the types of distribution vary across causes, so we cannot apply the same distribution assumption to each. In order to approximate each distribution, kernel density estimation was used to estimate the probability density function for each cause. One output of this method density of observations at each income level. Causes with a higher maximum density can be assumed to be relatively more specific to particular incomes than causes with a lower maximum density. As an example, figure 1.1 illustrates the distribution of weighted income associated with mortality for the cause neonatal sepsis, an income specific cause of mortality, and multiple sclerosis, which spans a larger income range.

Based on the ranking provided in Table 1.1, we could identify causes as being low, mid, or high income causes. This would provide a mortality road map of sorts by providing an expected burden shift as income grows. The expected income along with the standard deviation and max probability density of each cause provide insight into expected income or groups of incomes for each cause. This is particularly useful for interpreting the expected income of causes that fall within the mid income range. Understanding the relative distribution of the cause allows us to determine whether the cause is middle income specific, or whether is spans multiple, or even all income groups, putting its expected income in the middle.

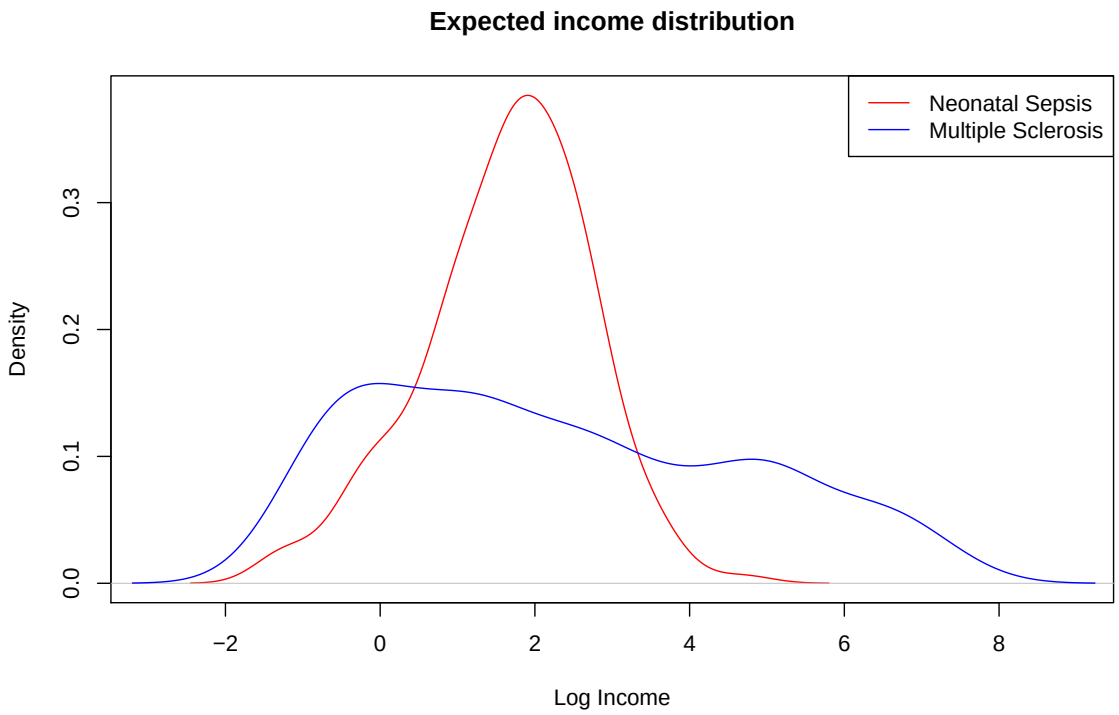

FIGURE 1.1. Examples of a income specific cause of mortality vs. a burden that spans multiple income groups. Distributions are from 2010.

Figure 1.2 illustrates how the social value of the burdens changes across the income landscape. Burdens that are primarily associated with high income countries are the burdens that have the smallest social value in terms of years of life lost due to the burden. Burdens in low income countries are those that primarily afflict young individuals and lead to the largest number of years of life lost. It would seem that as income rises, health related resources are allocated to their most productive use in terms of managing burdens with high social value. Or, burdens that are relatively more easily prevented and controlled are prioritized.

From table 1.1 we also get a sense of how burdens are prioritized by public and private health spending. Looking at the top ten burdens sorted by increasing expected income, all but malaria which is likely geographically specific, has a high max density suggesting that the mortality distribution is tight and heavily skewed to lower income countries or individuals.

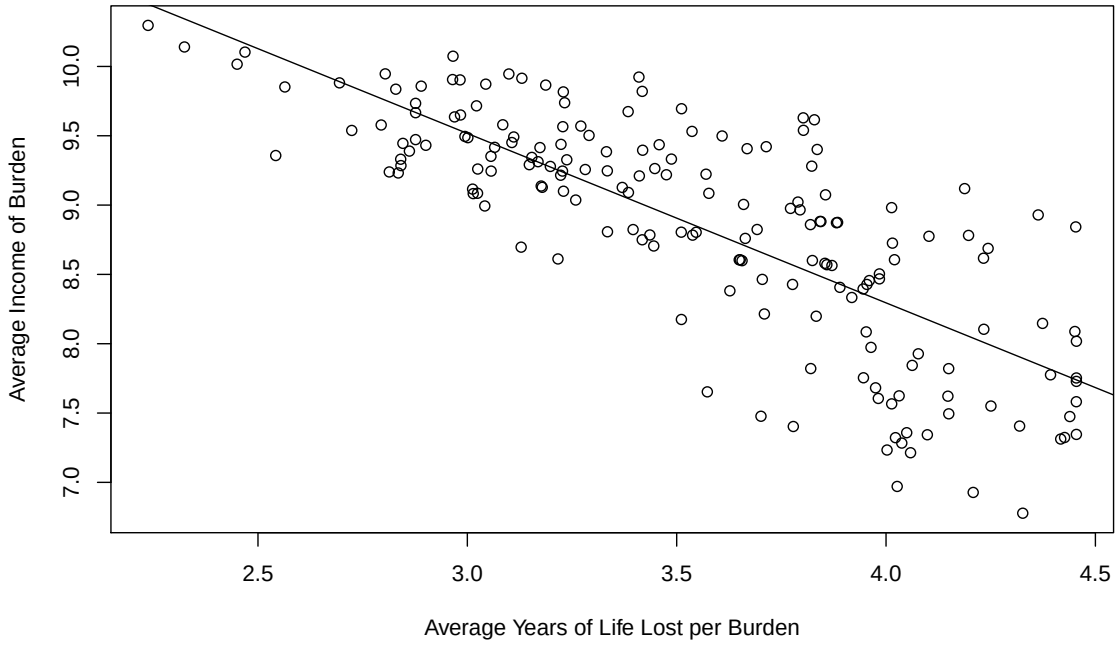

FIGURE 1.2. As the average income of a burden rises, the years of life lost due to the burden declines

[2]

It may be that the burdens are simply more often found in lower income countries, which would be the case for malaria, but others like the various maternal burdens associated with childbirth and preventable diseases could be found anywhere. The mortality risk of all ten, aside from malaria is drastically reduced when incomes grow, even in relatively small amounts.

The low expected income and low standard deviation of the income distribution suggest that as incomes rise, mortality rates for these burdens declines dramatically. This may be due to individuals having greater access to relatively low cost vaccines for the preventable diseases and medical facilities, or trained medical professionals for the routine medical procedures or childbirth. This suggests that as income grows either public or private dollars are being

prioritized to combat these relatively easily preventable burdens, likely a combination of the two.

Figure 1.3 illustrates this decline of prioritized and preventable burdens compared to a relatively income immune burden, Stroke. It is apparent that as income grows, the mortality rate of stroke victims remains relatively constant through all income groups, even increasing marginally during the middle income stages. Tetanus and obstructed labor mortality rates, however, decline quickly as income grows and settle and a relatively low rate, significantly lower than at the lower income stages.

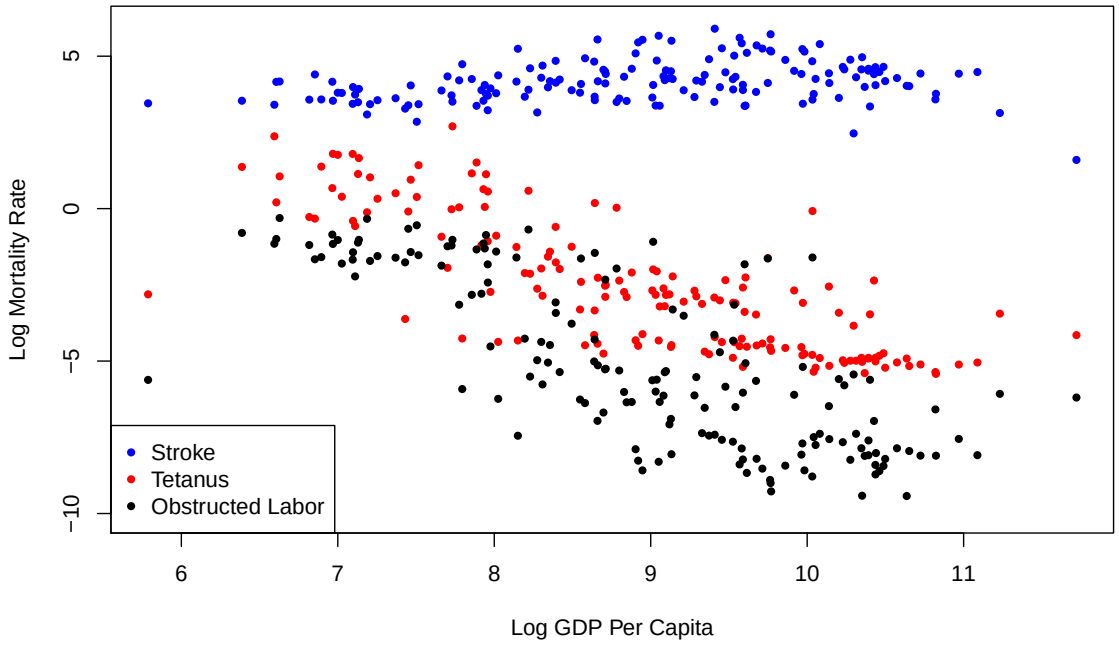

FIGURE 1.3. As income per capita rises, there is a sharp decline in tetanus and obstructed labor mortality rates, while the stroke mortality rate remains relatively constant.

Intuitively, there would seem to be a relationship between income and the mortality rates of specific burdens, such as tetanus and obstructed labor. This could be due to increased

public and private investment into healthcare as disposable income grows. The reverse relationship is also interesting while more difficult to measure. As the mortality rate of disease and other burdens falls, especially burdens that disproportionately affect working age individuals, there may be a measurable benefit to economic growth. As mortality rates fall and overall health improves, productivity may improve, the labor force may grow, the number of years individuals spend in the labor pool may also grow along with life expectancy. This could create a cycle of sorts where income growth improves health, which in turn boosts income.

We present a theoretical model which may explain the relationship between income and health at the household level. We then attempt to identify the strategy that would be needed to isolate and quantify this relationship from both directions, i.e. from income to health, and from health to income.

1.4. Household production and burden prevention

We start with a standard household production model that follows [17]. Household utility, u, is derived from consumption, c, and the overall health of the household. We assume that health is determined by the morbidity rate of individual burdens, b. We also assume for simplicity that households only suffer from one burden at any given time. The household utility function is then defined as

$$u = u(c, b) \tag{1.2}$$

We assume that consumption increases utility but at a decreasing rate, and that burden morbidity reduces utility at a decreasing rate. Equation 1.2, then, produces the following first and second order conditions: $u'(c) > 0$, $u''(c) < 0$, $u'(b) < 0$, and $u''(b) > 0$. The amount of income available for household consumption is constrained by the following budget equation

$$c = y - \frac{p_h}{p_c}h \tag{1.3}$$

where y is the available budget, c is the amount spent on consumption, h is the amount spent on preventative measures which could be healthcare or other safety precautions, and p_c and p_h are the prices of consumption and health care, respectively.

Assume that production occurs at the household level and that the household owns the factors of production, k and l which are transformed into output, y. Beyond the factors of production, we assume that household health, in the form of burden morbidity b, directly influences output as well as other potential exogenous factors, X. Household output is defined by the following production function

$$y = f(k, l, b, X) \tag{1.4}$$

where all factors of production have diminishing marginal effects on output. The first and second order conditions are as follows: $f'(k) > 0, f'(l) > 0, f'(b) < 0, f''(k) < 0, f''(l) < 0,$ and $f''(b) > 0$.

The burden morbidity rate is influenced by investment into preventative measures h, as well as public investment into preventative measures, denoted by g. Our model differs from that in [17] with the addition of g. Other exogenous factors such as geography, development stage, demographics, etc. may also influence the burden morbidity rate. We denote these potential exogenous factors as Z.

$$b = b(h, g, Z) \tag{1.5}$$

Equation 1.5 produces the following first and second order conditions: $b'(h) < 0, b'(g) < 0, b''(h) > 0,$ and $b''(g) > 0$. This means that investment into preventative measure both from the household and the public reduce burden morbidity rates but at a diminishing rate.

Substituting equation 1.5 into equation 1.4, and substituting equation 1.4 into equation 1.3 yields

$$c = f(k, l, b(h, g, Z), X) - \frac{p_h}{p_c} h \tag{1.6}$$

which when substituted, along with equation 1.5, into equation 1.2 forms the household's utility maximization problem. The decision variable is the choice of investment into preventative measures, h.

$$Choose \quad h \quad to \quad max \quad u(f(k, l, b(h, g, Z), X) - \frac{p_h}{p_c} h, b(h, g, Z)) \tag{1.7}$$

The first order condition with respect to the choice variable set equal to zero produces the following relationship

$$\frac{\partial u}{\partial c}\left[\frac{\partial f}{\partial b}\frac{\partial b}{\partial h} - \frac{p_h}{p_c}\right] + \frac{\partial u}{\partial b}\left[\frac{\partial b}{\partial h}\right] = 0 \tag{1.8}$$

Solving equation 1.8 for the price ratio between consumption and preventative measures yields

$$\frac{\partial f}{\partial b}\frac{\partial b}{\partial h} + \frac{\partial u/\partial b}{\partial u/\partial c}\left[\frac{\partial b}{\partial h}\right] = \frac{p_h}{p_c} \tag{1.9}$$

which yields the following relationships

$$\frac{\partial f}{\partial b}, \quad \frac{\partial b}{\partial h}, \quad \frac{\partial u}{\partial b} < 0, \quad and \quad \frac{\partial u}{\partial c} > 0$$

The first term in equation 1.9 is the marginal impact of investment into preventative measures on per capita output. The second term is the marginal impact of investment into preventative measures on household utility. Both terms are positive. The overall benefit is then set equal to the marginal cost of private investment, p_h/p_c.

From equation 1.4, we see that the burden morbidity rate negatively impacts household production. We assume that the inverse relationship also exists for some burdens. This can be illustrated by solving equation 1.5 for h showing that $h = (y - c)(p_c/p_h)$. Combining this identity with equation 1.5 yields the following relationship

$$\frac{\partial b}{\partial y} = \frac{\partial b(h, g, Z)}{\partial h}\frac{\partial h}{\partial y} < 0 \tag{1.10}$$

Likewise, public investment also has an impact on household burden morbidity rates such that

$$\frac{\partial b}{\partial g} = \frac{\partial b(h, g, Z)}{\partial g} < 0 \tag{1.11}$$

Depending on the nature of the burden the marginal effect of income ,$\partial b/\partial y$, may be larger than the marginal effect of public investment, $\partial b/\partial g$, or vice versa. Some burdens may require large scale efforts to effectively prevent morbidity, such as infrastructure improvements, safety regulation, or the benefits of heard immunity stemming from mass vaccination against diseases like measles. Other burdens may depend more on private investment such as medication for things like asthma or high blood pressure.

We assume identical preferences and factor endowments across households in each country, allowing us to use representative households for each country in each time period. To account for the potential of reverse causality between income and burden prevalence, we would need to estimate equations 1.4 and 1.5 as simultaneous equations. For burdens that

do not exhibit reverse causality, we would estimate equation 1.4 using either OLS or 2SLS where appropriate.

1.5. Identification Strategy

Ideally, the goal of this paper would be to explore the directional causal relationship between income and individual health burdens, and those burdens and income. This would allow for a direct comparison of the relative impact of certain health burdens on the expected income growth of individuals, and how they compare to other burdens. This understanding could lead to prioritization of health related spending on burdens that would yield the largest marginal benefit in terms of social value. In addition, understanding how income growth and spending directly, or indirectly impacts burden rates would provide insight into improving health spending strategies.

Establishing this causal relationship, however, is difficult to do as there are likely unobservable influences which will affect the outcome of estimation. Examples of methods needed to attempt to identify these relationships would income sample selection control methods as more traditional methods, such as double-blind randomized experiments are simply not available. Proper sample selection should introduce adequate variation in our variables of interest. In addition, we would need to control for other factors that may be correlated with our variable of interest in each structural equation. Failing this, we likely need an Instrumental Variable (IV).

The instrumental variable method for estimating causal relationships is a very popular with the IV estimates commonly viewed as recovering the local average treatment effect (LATE) among the population of compliers, or those whose treatment status is influenced

by the IV [18]. This relies on the exclusion restriction which states that the instrumental variable used does not have any direct effect on the dependent variable or any indirect effect through omitted variables. This assumption is necessary for any convincing instrument, but is often violated [19, 20].

One method of obtaining convincing instruments is using Natural Experiments, or examining the outcome measures for observations in the treatment and control groups which are not assigned randomly. Given the lack of randomization, the source of variation is gleaned from what would resemble an experimental design [21, 22]. In our case, there is potential for IVs which are correlated with health, but not with income, but the opposite provide less options. Things like climate, storm frequency, elevation, rainfall, snowfall, etc. would all be likely correlated with health [23]. For example, warmer tropical climates are more prone to disease such as malaria, or typhoid. Countries with higher rain or snowfall may experience more auto accidents or job related accidents, etc. In terms of longitudinal temporal variation, climate change may be a good option. The change in global temperature across the globe has had impacts of varying degrees based on location. This has potentially led to burden profile shifts and rates.

Other empirical attempt to identify the causal link between income and health have included instruments of lottery winnings of Swedish lottery players[24], disability pensions in Austria [25], firm-specific wage components [26], and more.

Attempts to identify the relationship between specific burdens and income are less plentiful, though to exist. [27] for example use what is called Malaria Ecology as an instrument for malaria risk which consists of temperature, mosquito abundance and vector specificity. It is assumed to exogenous to public health interventions and investments. The authors find

that malaria risk directly affects per capita income. [28] use food prices as an instrument for calorie intake, finding that calorie intake does impact wage offer. Others, such as household wealth, community health infrastructure, and local food prices are used to instrument for disability days identify the relationship between health and wages earned [29].

In order to ensure the exclusion restriction of IV used in this analysis, we would need to identify a variable that would be correlated with health but not income for equation 1.4, and a variable that is correlated with income but not health for equation 1.5. This is relatively easier for burdens that are geography or climate specific such as malaria, but more difficult for non geographic or climate specific such as obstructed labor. One options for something like obstructed labor could be physical build, or identifying certain body types that would be more susceptible to such complications, and potentially the races, or regions where those physical builds are more abundant. Alternatively for an instrument that is correlated with income but not health, there seems to be several possible options such as geography, climate, and other natural experiments like lottery winnings, etc.

Another relationship that needs to be considered is how burdens move together. It is true that many burdens may be correlated, meaning that if measures were taken to reduce the prevalence of a specific burden, the prevalence of other burdens may fall along with it. [30] find that patients with type-2 diabetes with no prior myocardial infarction have the same risk of myocardial infarction as non-diabetic patients that do have a history of myocardial infarction. It stands to reason, then, that by reducing the prevalence of type-2 diabetes will also lead to lower prevalence of heart disease. If we are interested in identifying the isolated relationship between income and mortality or mortality and income of specific burdens, we

will need a way to address this multicollinearity, otherwise our estimates could be including the impacts of other burdens as well.

Clearly, this quickly becomes a daunting exercise as each burden or groups of burdens would likely require their own specific instrumental variables in order to satisfy the exclusion restriction. We would also need to consider instruments that are specific to a single burden to limit the cross burden correlation. If burdens cannot be distinguished in any meaningful way, highly correlated burden clusters could be estimated to identify the relationship between income and the burden cluster, and the other way around. Though this is less ideal as the interpretation is less specific when talking about the individual burdens in the cluster.

Assuming that convincing instruments could be identified for one or more burdens, we would then need to account for the potential for reverse causality. This could be done by employing a seemingly unrelated regression (SUR) strategy where health and income equations would be estimated simultaneously. Three stage lease squares (3SLS) could be used where first, instruments are estimated, and then used in the SUR estimation. This relies on the assumption that each system is properly identified and that rank and order conditions hold for each system. Hausman tests for endogeneity and reverse causality could be performed to ensure that the reverse causality is in fact present, otherwise a two stage least squares (2SLS) regression method could be used.

In the next section we outline a potential estimation strategy assuming that all necessary restrictions have been met, e.g. exclusion restriction, reverse causality, etc.

1.6. Estimation Framework

The potential empirical approach to estimate equations 1.4 and 1.5 would be using 3SLS system of equations model. The following generalized versions of equations 1.4 and 1.5 would be used

$$y_{it} = \beta_0 + (\phi_0 - \beta_0)D_{it} + \beta_1 \hat{b}^*_{it} + \gamma_{it} X_{it} + \alpha_j R_j + \epsilon_{it} \tag{1.12}$$

$$b_{it} = \eta_0 + \eta_1 \hat{y}_{i,t-1} + \eta_2 \hat{g}_{it} + \delta_{it} Z_{it} + \alpha_j R_j + \zeta_{it} \tag{1.13}$$

where for equation 1.12, y_{it} is the log income per capita, b_{it} is the log burden mortality rate, X_{it} is a vector of exogenous regressors, R_j is a vector of six regional dummy variables, and ϵ_{it} is the error term capturing all unobserved effects across countries and time. The variable D_{it} follows the form from [31] where $D_{it} = 1$ if $b_{it} = 0$ and $D_{it} = 0$ if $b_{it} > 0$, and $b^*_{it} = Max(b_{it}, D_{it})$[3]. For equation 1.13, b_{it} and R_j are the same as in equation 1.12. Income is now lagged, $y_{i,t-1}$ to account for the assumed recursive effect of income on burden mortality [32]. Meaning, changes in income take one year to impact burden mortality rates. The variable g_{it} is the per capita public spending on preventative measures. The variable Z_{it} is a vector of exogenous regressors that influence burden prevalence. Finally, ζ_{it} is an error term. The hats in equations 1.12 and 1.13 indicate that $\hat{b}_{it}$ and $\hat{y}_{i,t-1}$ are instrumental variables.

The regression method 3SLS assumes that one or more right hand variables are endogenous, as well as assuming that there is some form of reverse causality. For many burdens these may be justified assumptions. [17], for example, find this to be the case for malaria and per capita income. The authors use 3SLS which is shown to be consistent and efficient, opposed to standard OLS and 2SLS. The assumption is that most burdens will exhibit endogeneity

[3]The variable D_{it} is used to efficiently estimate equation 1.12 when values for the burden are zero as taking the log of zero produces estimation errors.

and simultaneity, meaning that there is some form of omitted variable bias or measurement error as well as reverse causation, or that income also influences burden prevalence.

We would also need to perform a number of diagnostic tests such as Durbin-Watson to test for autocorrelation, Breush-Pagan to test for heteroscedasticity, and Shapiro-Wilk to test for abnormal regression residuals.

1.7. Discussion

We believe this paper is a contribution to the literature by providing a basic income growth burden transition map. We show where individual burdens fall on the income scale and what countries could potentially expect in terms of which burden mortality rates will decline as income grows, which will increase, and which will likely remain constant. We show that burden mortality rates decline at different rates as income grows, allowing for policy makers to potentially prioritize burdens where public or private investment yields relatively high social returns. An interesting observation is that the vast majority of burdens that fall in the low income range disproportionately affect young individuals, ages 0 to 14, and those of working age, 15 to 65. The social value of reducing the burden associated with these burdens, is then very high as the years of life lost are largest for these burdens.

Previously, the literature has overwhelmingly focused on the relationship between income and aggregate health measures such as life expectancy or infant mortality, or single burdens in isolation. While important relationships to explore, they may not be entirely actionable from a policy makers perspective. The task of 'increasing life expectancy' in order to increase income growth is ambiguous without providing any sort of idea of what to tackle first, second, etc. to maximize the social return of scarce resources invested. Understanding where burdens lie on an income scale and how income specific they are, will potentially inform health related

investments. It may also help policy makers anticipate incoming burdens as income grows allowing for proactive prevention or mitigation strategies.

While our analysis is purely a summary of the available data, we believe it provides an invaluable snapshot of the burden mortality rate transition through the development phases globally. The insight for some burdens is more clear than other. Some burdens, such as tetanus which is geographically universal see a rapidly declining impact on mortality as health grows. It also suggests that the strategy may also be universal so that countries could learn from each other to improve the mitigation strategy. This suggests that it may be a good burden to be prioritized early on in low income countries to maximize investment returns. Others, such as malaria are geographically specific so that insights would also likely be specific to countries where malaria is prevalent. Further, strategies for malaria would likely vary by location as the key malaria factors such as temperature, mosquito density, storm frequency and severity vary by location as well. And other burdens, such as stroke seem to span all income groups equally, suggesting that as income grows, stroke risk remains constant. This is not to say that no investments should be made in stroke mitigation, just that the social returns may not be as immediate or large as those associated with other, more income specific burdens.

Additional work would be needed in order to empirically estimate the relationship between each burden and income in order to properly optimize a longitudinal burden mortality reduction strategy. We stop short of empirically exploring these relationships but we do develop a theoretical framework with which the impact of an individual burden on income growth or vice versa could be identified, assuming all necessary identification conditions are met. The literature does provide empirical estimates of a few of these relationships, but

far too few to guide any largescale health investment strategy. This becomes a substantial endeavor as satisfying the exclusion restrictions would likely be different vary by burden or burden clusters.

In addition, further empirical research could potentially explore the difference between public and private health investment and their respective relationships with different burdens. It is likely that some burdens would respond more to public investment campaigns or regulations while other may respond better to private investment. Understanding which burdens may benefit from public vs. private investment (or vice versa) could lead to more effective public health initiatives. Public health policy makers may want to invest more into awareness campaigns to spur private investment for certain burdens while investing into vaccination campaigns, for example, for other burdens.

This paper provides a base upon which further research can build to extend understanding of the relationship between health burdens and economic growth. We have shown that additional analysis and examination is warranted and would be vital to better understand how income is related to mortality burden and expected burden profiles, which as of yet has not been attempted at such a large scale.

Essay #2: Interspecific Population Management and Disease Control

2.1. Introduction

Disease can play a large role in crafting management strategies surrounding many human, wildlife, or livestock issues. Management goals may be to minimize human exposure to disease, maximize livestock production, or to minimize damages. While various benefits arise from managing disease, it may be very costly to do so, requiring managers to weigh the trade-offs of any particular strategy [33, 34]. Controlling disease would require less effort if outbreaks could be anticipated by providing protection prior to the outbreak and limiting management between outbreaks. The challenge arises due to the uncertainty of outbreak timing, especially within wildlife populations. This leads to either constant disease protection to ensure minimum losses, no disease protection to minimize management cost, or perhaps a hybrid by responding to outbreaks to try and reduce the extent of damage caused. The former will minimize damage though at a higher ongoing cost. The latter will minimize management cost at the risk of high losses in terms of lost livestock or human contact. The third option may be successful at mitigating risk at a reduced cost though if a disease is aggressive, reaction times could be too large to provide any real benefit.

The purpose of this paper is to develop an ecological model to examine the disease management problem when the wildlife host only provides value in that it sustains a separate species with high non-market/intrinsic value. In our case due to potential extinction. We examine the effect of geographic (spatial) protection vs. physical protection against disease transmission. Specifically, the model is developed to analyze management strategies for mitigating the impact of sylvatic plague on prairie dog populations which are the primary diet of the target species, black-footed ferrets. Management strategies include a spatially

applied insecticide which kills the fleas that act as the plague vector, and oral vaccination designed to protect the prairie dogs themselves against transmission. We find that there exists a threshold target ferret population, below which oral vaccination is more cost effective, and above which, insecticide is more cost effective. The threshold level is sensitive to biological and economic parameters.

The spread of infectious disease from wildlife to domesticated animals is a major worldwide problem. Wildlife related diseases that spread to livestock, for example, have the potential to cost billion of dollars. The USDA has estimated that a Foot-and-Mouth Disease (FMD) outbreak in the UK in 2001 cost $13 billion and reduced the UK economy by 0.3%, and that a similar outbreak in the US (which is considered FMD free), could cost billions in first year alone, plus the ongoing costs of losses, control, and management [35]. Beyond the initial and ongoing losses, costs occur in the form of increased trade restrictions, and biosecurity measures. In 2000, Michigan lost its accredited Bovine Tuburculosis free status, which cost an estimated $22 to $74 million in the proceeding five years in the form of more stringent regulation and cattle losses [36]. [37] provide a table of 26 wildlife diseases that pose a risk to livestock as well as humans.

A manager's optimal choice of intervention will likely depend on the desired outcome, whether it be to eliminate the disease entirely, maximize the size of a particular population, or simply limit the impact of the disease. Population control has been identified as an effective method of disease elimination by reducing the population below a theoretical threshold, beyond which the disease can no longer replicate, leading to elimination [38]. The effect of population control on wildlife disease dynamics has been significantly explored in the ecological literature [33]. While population control can be an effective tool to achieve disease

elimination or reduction, reduced population size may not be desirable if the target species is relatively valuable. Managers may wish to reduce disease burden while simultaneously maximizing the wildlife population size because of indirect value. Other protection methods include wildlife vaccination programs [39, 33], large scale environmental activities [40], and supplemental feeding [41–43].

For a manager tasked with maximizing a livestock or wildlife population, the required threshold for disease eradication may not be feasible. Further, if the primary disease vector exists within an unmanaged species, eradication of the disease within the target population may only be temporary. This leads to a constant risk of exogenous introduction.

The manager's choice of intervention should also consider the role of interaction between wildlife species when determining the management strategy [44]. Literature surrounding interspecific competition has primarily focused on pest species control, often in the form of harvesting or other removal methods and the spillover effects from the management of pest species to other wildlife species [45, 46]. The ecosystem management literature that accounts for stock-dependent species interaction primarily deals with optimal harvest rates [47–49], though has recently grown to include the role of habitat loss and creation [50, 51].

A specific example of interspecific population dynamics and disease control can be found in reintroduction efforts of the black-footed ferret (Mustelanigripes). The black-footed ferret was thought to be, and was officially declared extinct in 1979. In 1981 a ranch dog in Meeteetse, Wyoming, returned home with a dead ferret. The owners notified Wildlife Services officials who located that last known remaining ferret colony [52]. A successful captive breeding program led to the reintroduction of approximately 4,500 ferrets across 24 sites in the US and Canada [53]. A major impediment to the successful reintroduction of black-footed

ferrets is sylvatic plague (Yersinia pestis) epizootics in prairie dog (Cynomys) populations. Plague epizootics have limited ferret habitat with sufficient prey as up to 90% of the ferret's diet is composed of prairie dogs, with mice and voles being consumed with a much smaller frequency [Campbell Iii et al., 1987]. This dependence on prairie dog populations can lead to large reductions in the ferret population or even extirpation with the possibility of whole colonies being wiped out within a single breeding season [54, 55]. In order to prevent potential plague outbreak, Wildlife Services routinely applies insecticide throughout existing reintroduction sites.

As an alternative, a potential oral vaccination is also being developed for use among prairie dog colonies, with research ongoing [56–58]. Baits containing this vaccine could be distributed by aircraft or vehicle to specific prairie dog habitats. Oral vaccination, as opposed to insecticide, would provide permanent protection for prairie dogs against plague while insecticide degrades and is only effective for animals living within the coverage area.

These results could extend to human side disease prevention. Human disease can be controlled in several ways including a more spatial approach of border control vs. a more individual approach of mandating vaccinations. A social planner may be interested in finding the optimum balance between spatial and individual disease protection that maximizes overall social net benefit.

2.2. A Model of Indirect Population Management Through Disease Control

2.2.1. The Ecological Model.

We model the two treatment options separately since most current management strategies do not incorporate the two and likely would not combine

them for simplicity sake. The two options are comparable by their achieved outcomes when subjected to either budget constraints or target abundance levels. We now discuss the modeling approach for both dusting and oral vaccination.

2.2.1.1. *Dusting.* It is assumed that the host prairie dog (PD) population, N_{PD}, is closed to migration and contained to a fixed geographical area. This is a reasonable assumption as populations can be vast distances apart and immigration is minimal. A modified SEIR compartmental framework was used to model the disease dynamics. This stands for susceptible, exposed, infected, and recovered (SEIR), which is a common disease dynamic modeling approach. Compartmental models are simply mathematical frameworks used to stratify a population into different health states. The model includes assumptions which govern the interaction of individuals in each state and the movement between states. The possible states of individuals within the host population are susceptible S, infected I, and protected P [4]. The current intervention strategy used to protect the host from plague is the application of a powdered insecticide called Delta Dust. The insecticide (dust) is applied (dusting) to the burrow openings and surrounding area within a colony of the host. All animals living within the dusted area are assumed to be protected from the fleas that serve as the primary disease reservoir [59]. Aggregate population of the host then, is simply $N_{PD} = S + I + P$. Changes in S, I, and P are defined as

$$\dot{S} = G(S, L, N_{BFF}) - C(S)\beta SI - \theta(S, P) - \delta S - \omega(S, P, L) \tag{2.1}$$

$$\dot{I} = C(S)\beta SI - \theta(S, P) - \delta S - \alpha I \tag{2.2}$$

[4]There is no recovered class as sylvatic plague is chronic with a mortality rate of approximately 100 percent [Cully Jr, 1997]

$$\dot{P} = Z(P, L, N_{BFF}) - \theta(S, P) - \omega(S, P, L) \tag{2.3}$$

Where G and Z (defined below) are density dependent logistic growth functions which are influenced by the aggregate predator black footed ferret (BFF) population, N_{BFF} . This relationship incorporates a predator prey dynamic where the predator black-footed ferret population, N_{BFF}, negatively influences the host (prey) prairie dog population,N_{PD}, such that

$$G = r_{PD}S\left(1 - \frac{S + \gamma N_{BFF}\frac{S}{(S+P)}}{(1 - \frac{L}{K_L})K_{PD}}\right) \tag{2.4}$$

$$Z = r_{PD}P\left(1 - \frac{P + \gamma N_{BFF}\frac{P}{(S+P}}{(\frac{L}{K_L})K_{PD}}\right) \tag{2.5}$$

The parameter,γ, in equations 2.4 and 2.5 attempts to capture the effect of the aggregate predator population on the aggregate prey population. As the predator population increases, a larger portion of the prey population is hunted, leading to a decline in the host (prey) population. Assume then,that $\gamma > 0$, meaning that for any $N_{BFF} > 0$, $N_{PD} < N_{PD}^{max}$, where N_{PD}^{max} is the prey population achieved when there are no predators.

Given that protection refers to a geographic area that has been treated against the diseased reservoir, all offspring born to mothers within the protected area, are assumed to also be protected from the disease. Changes in the aggregate protected land area is defined as

$$\dot{L} = e_d K_L(1 - \frac{L}{K_L}) - \phi L \tag{2.6}$$

where K_L is the total colony area, or the total possible area available for dusting, and L is the total stock of dusted land. The term L/K_L, then, is the proportion of total area that is dusted at any point in time. Managers choose the proportion of total land area to dust e_d, for any given period. Where in our case the period is a year, so effort is applied annually. The dusted area provides protection against the disease to animals living within that area, while animals not in the protected area are still susceptible. Movement between protected and none protected areas is allowed and is described by equation 2.9 below. The terms $(1-(L/K_L))K_{PD}$, and $(L/K_L)K_{PD}$ in the denominators of equations 2.4 and 2.5 account for the fact that population density may vary between the protected and non protected areas resulting in different growth rates. The dusted area reverts back to unprotected area at rate ϕ. It is assumed that the manager does not know what areas have reverted to unprotected status, therefore, the manager will randomly dust a given proportion e_d, of the total area K_L every period. This means that some still protected area may be dusted again. A fixed value of e_d=0.5, for example, means that 50% of the total land area will be dusted in every period. If the population is uniformly distributed across the landscape, then this means that half of all the host population will become protected. At least in period one. In subsequent periods, an effort level of e_d=0.5 may not provide coverage for half of the remaining susceptible animals as the manager may be redundantly dusting still protected areas.

Movement between the S and P classes stemming from dusting effort and dust degradation is governed by the equation $\theta(S,P)$. The net movement of animals between classes due to dusting effort e_d, and degradation ϕ, takes the following form

$$\theta = e_d(S+P) - \phi P \tag{2.7}$$

The transmission function takes the form presented by [43], where $C(S)$ is the contact function which determines the overall probability of an animal contracting the disease such that

$$C = \frac{1 - \epsilon - \epsilon S}{S} \tag{2.8}$$

The parameter $\epsilon \in (0,1)$ represents the degree of density dependence of the disease transmission. If $\epsilon = 0$ then the transmission equation becomes frequency dependent. If $\epsilon = 1$, the transmission becomes density dependent [38]. It is assumed that in reality $0 < \epsilon < 1$. The variable β is the disease transmission rate.

The function $M(S, P, L)$ governs the movement of animals between the protected and non protected areas in order to equalize population density. This specification assumes that a population decline in one area (in our case, due to disease) causes migration pressure due to the change in relative densities. Net migration is defined as

$$\omega = \eta \left(\frac{S}{(1 - L/K_L)K_{PD}} - \frac{P}{(L/K_L)K_{PD}} \right) (S + P) \tag{2.9}$$

where η is a dispersion parameter, or the rate at which the migration occurs. If $\eta = 0$ then no migration occurs. If $\eta = 1$ then migration occurs instantly every period. We would assume that $0 < \eta < 1$ so that there is some lag in the migration from area to another. This specification is assumed in other ecological models which incorporate migration between locations (e.g. [60] and [61]) and captures the findings in [62], that feral cats in neighboring populations immigrate due to resource abundance, and in [63], that female deer migrate according to resource availability relative to density.

The parameter, δ, represents the constant exogenous threat of disease introduction from outside disease vectors. In the case of sylvatic plague, the primary form of transmission among wildlife is through flea bites. This means that even if the disease is not present or is eliminated, it is introduced or reintroduced to the susceptible class at any time at rate δ. The parameter α is the disease-specific mortality rate.

Finally, changes in the aggregate predator population are defined as

$$\dot{N}_{BFF} = r_{BFF} N_{BFF} \left(1 - \frac{N_{BFF}}{K_{BFF}(S, P)} \right) \tag{2.10}$$

where the carrying capacity of the predator population is a function of the healthy prey population. Assume that the predator's diet is almost exclusively comprised of the prey, so that if the prey population were to fall to zero, so would the predator population. This dynamic is captured in the modified predator carrying capacity: $K_{BFF} = \omega(S + P)$ [64]. Where ω represents the proportional relationship between the predator and prey populations, i.e., the maximum sustainable number of predators, K_{BFF}, for any given healthy prey population $(S + P)$. For simplicity, assume further, that the predator population does not feed on infected or dead host animals. This assumption implies no disease transfer from the host to the predator population or to protected animals.

2.2.1.2. *Oral vaccination.* Assume that another method of disease control exists in the form of oral vaccination. Baits containing a vaccine against the plague can be dropped throughout the colony. These baits are eaten and provide temporary, and sometimes permanent disease protection for the animal. To simplify, we assume that the protection afforded from the oral vaccination is permanent given the relatively short lifespan of the host species.

To account for the modified dynamics associated with oral vaccination, equations 2.1, 2.2, 2.3, and 2.10 are rewritten as

$$\dot{S} = Y(S, V, N_{BFF}) - C(S, V)\beta SI - O(S, V) - \delta S - \mu S \tag{2.11}$$

$$\dot{I} = C(S, V)\beta SI + \delta S - \alpha I \tag{2.12}$$

$$\dot{V} = O(S, V) - \mu V \tag{2.13}$$

$$\dot{N}_{BFF} = r_{BFF} N_{BFF} \left(1 - \frac{N_{BFF}}{K_{BFF}(S, V)}\right) \tag{2.14}$$

In this scenario, protection from the disease is no longer geographic. This means that protection is not passed from mother to offspring. There is also no longer migration from a protected to non protected area as it is assumed that baits are distributed uniformly across the landscape, and therefore, successfully vaccinated (and non-vaccinated) animals will also be uniformly distributed. This is a reasonable assumption as currently, oral vaccination are often dropped from aircrafts using machines that drop baits at equal intervals and in equal quantities while the flight pattern moves uniformly across the landscape. Growth is again logistic with a predator prey dynamic and takes the following form

$$Y = (S + V)\left(\pi - r_{PD}\frac{S + V + \gamma N_{BFF}}{K_{PD}}\right) \tag{2.15}$$

where π is the birth rate of the host population and μ is the mortality rate. Given that we assume no recovery and 100% mortality, $\alpha = 1$, there is no natural growth or mortality in I. The contact rate is not determined by overall population density as susceptible and vaccinated animals are interspersed across the landscape. The contact function is now written as

$$C = \frac{(1 - \epsilon + \epsilon S)}{S + V} \tag{2.16}$$

where the contact rate is a function of aggregate density as animals are no longer segregated.

The protection function is also modified in that effort is no longer applied to a geographic area, but rather, is a choice of the number of oral baits to uniformly distribute over the landscape. It cannot be assumed that animals will always have the opportunity to eat a dropped bait, even if one bait is dropped per animal. It must be assumed that some animals, as well as already vaccinated animals, may hoard baits and eat more than one, leaving none available for other susceptible animals. We then account for the increasing marginal costs associated with vaccinating animals. Let the proportion of susceptible animals vaccinated each period for a given number of baits distributed, ev, be defined as

$$P(ev) = 1 - e^{-\lambda \frac{ev}{(S+V)}} \tag{2.17}$$

where $P(ev) \in (0, 1)$, and the term $ev/(S+V)$ is the number of available baits per animal, a measure of "bait density". The parameter λ is a measure of the bait success. Equation 2.17 can also be interpreted as the individual probability that each remaining susceptible animal will become vaccinated given a certain number of baits distributed. The total number of newly vaccinated animals can then be written as: $O(S, V) = SP(ev)$. Figure 2.1 illustrates

the probability of vaccinating an animal for three hypothetical values for λ. As λ decreases for any given number of available baits per animal, the probability of successful oral vaccination also declines. For a fixed value of λ, the probability of successful oral vaccination increases with the number of baits distributed across the landscape (ev). In order to prevent the possibility of one bait vaccinating more than one animal, $\lambda \in (0, 1)$ ensuring that one bait can at most, vaccinate one animal.

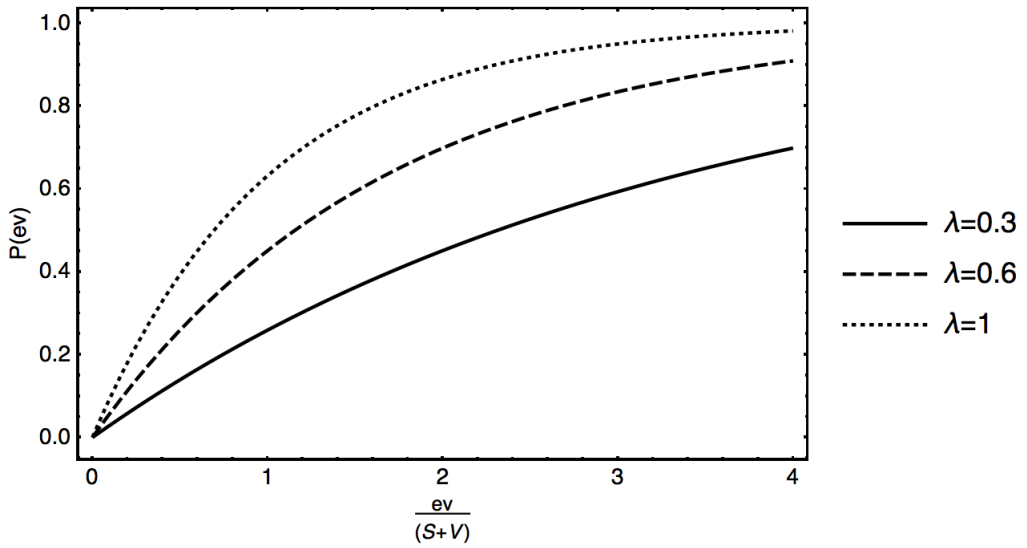

FIGURE 2.1. Probability of successful oral vaccination based on the number of baits dropped per animal on the landscape

In the next section we discuss our strategy to solve the model for specific management target outcomes including several different budget constraints as well as target population outcomes.

2.3. A Numeric Simulation of the Model

2.3.1. Motivation and parameterization. Ideally, we would construct a bioeconomic framework in order to solve for the optimal level of effort given the benefits less costs associated with management. The proposed model presents a scenario in which neither an analytic nor numerical solution is possible due to the complex nature of the differential

equations and the subsequent feedback rules. Though this may not be necessary as most managers are dealing with fixed budgets or set abundance goals already. This complexity requires that the model be analyzed in a non optimal way. Assume then, that a manager places sufficient value onto the predator population such that the associated costs of management are not considered the choice variable. In this scenario, the manager is constrained by a particular per-period budget that cannot be exceeded, and is assumed to be fully exhausted in each period. The objective of the manager is to maximize the predator population which provides some intrinsic value to society, through population management via disease control interventions. Disease control interventions include either dusting or oral vaccination.

Data used to parameterize the model were obtained primarily from the literature, annual Plague Management Reports from North Dakota, as well as from the The Black-Footed Ferret Recovery Implementation Team (BFFRIT) located in Wellington, Colorado. Plague Management Reports outline efforts to respond to and prevent plague outbreaks across North Dakota (ND). The plague management in ND consists of a coordinated effort by four federal agencies. Dusting efforts began in 2008 and have continued annually since then with support provided by the US Forest Service, Badlands National Park, the US Fish and Wildlife Service, and several NGOs [65]. The BFFRIT was created in 1996 as a multi-agency conservation effort led by the U.S. Fish and Wildlife Service, and serves as the main organization tasked with implementing efforts to promote recovery of the black footed ferret, an endangered species (blackfootedferret.org). Given the relatively recent interest in black-footed ferret recovery, the accuracy of many of the parameters may be limited due to lack of field studies. The results then, should be viewed as an example rather than an optimal management strategy to be implemented in the field. The results

do, however, provide interesting economic insights into the population management through indirect disease intervention and show which parameters most influence potential conclusions. Table 2.1 provides a list of all parameters, values, and sources.

TABLE 2.1. Parameter values used for the numerical example with their description and source

Parameter	**Descriptions**	**Value**	**Source**
S_0	Initial size of PD susceptible population	28,267	[65]
I_0	Initial size of PD infected population	0	Assumption
P_0	Initial size of PD protected population	0	Assumption
V_0	Initial size of PD vaccinated population	0	Assumption
L_0	Initial size of protected land area	0	Assumption
K_l	Total size of PD colony (acres)	3299	[65]
N_{BFF0}	Initial size of ferret population	178	Estimate
r_{PD}	Intrinsic rate of growth of the PD	0.07	$\pi - \mu$
π	Natural growth rate of PD animal	0.3	[66]
μ	Natural mortality rate of PD animal	0.23	[67]
r_{BFF}	Intrinsic rate of growth of the ferret	0.038	[68]
K_{PD}	Carrying capacity of the PD	56,400	Assumption
β	Disease transmission coefficient	0.073	[69]
ω	ferret population carrying capacity coefficient	0.0063	[64, 70]
ϕ	Protection degradation rate	1	Assumption
δ	Exogenous disease transmission rate	0.0001	Assumption
α	Disease related mortality rate	1	[71]
γ	ferret population effect on PD population	159	[64, 72]
ϵ	Disease contact parameter	0.01	Assumption
λ	Baiting success parameter	1	Assumption
η	Migration parameter	0.2	Assumption
c_D	Cost of dusting entire landscape	61,031	[65]
c_V	Unit cost of oral vaccine	2.87	[73]

We simulate a specific colony, called the Agate colony located in Conata Basin/Badlands area of North Dakota. The colony covers 3,299 acres of land and hosts an estimated population of 28,267 prairie dogs. [64] estimates that a minimum of 272.5 PDs are required to sustain one ferret family group, with 763 PDs being harvested annually per ferret family group in typical conditions. A ferret family group consists of one breeding female, their young for the year, and 0.5 adult males [72]. With an average litter size of 3.3, the average size of a ferret family group is 4.8 animals [70]. The carrying capacity coefficient ω, derived by dividing the average size of a ferret family group by the typical number of PDs reacquired

to support the group annually, and is interpreted as the number of ferrets that one PD can sustain annually. Assuming that the PD population is at steady state and the ferret population is at carrying capacity, we estimate an initial population of 178 black-footed ferrets ($S_0\omega$).

We are interested in comparing the black-footed ferret abundance outcomes for dusting vs. oral vaccination when the management budget is fixed at various levels. We are also interested in identifying specific dusting coverage levels and bait densities required to achieve specific black-footed ferret abundance outcomes. This could provide managers with an idea as to the most cost effective strategy given various goals. It could also identify the conditions under which one method would be more cost-effective than another. The proceeding sections will provide simulation results for maximum dusting efforts and oral vaccine densities given several potential budgets. We then compare specific ferret population outcomes and their required dusting and oral vaccine efforts. Finally, we perform a sensitivity analysis.

2.3.2. Population outcomes with fixed project budgets. Assume that a wildlife manager tasked with maximizing the ferret population over time faces a fixed budget constraint every period. The manager's decision is whether to use dusting or oral vaccine to achieve the desired outcome, assuming the entire budget is spent every period. We explore the potential outcomes using five potential budgets. In 2014, during the annual dusting effort of the Agate colony, 3,299 acres were dusted (100% of the total available acres) at a total cost of \$61,031 [65]. Assume that this budget represents the maximum potential budget that a manager may face, B_{max}. We propose 10 budget scenarios of 10% increments of B_{max}.

Given the potential budgets, a manager chooses the highest affordable dusting effort or bait density to apply to the PD colony each period. The outcome of interest is the population

of the ferret in the final period, which is assumed to be the steady state. In addition, we are interested in the path that the population takes before reaching steady state. This will be measured by the sum of per period ferret populations as a measure of total biomass. As an example, using B_{max}, figure 2.2 illustrates the path that ferret populations take before settling at the assumed steady state. Results of the oral vaccination scenario are highly dependent on the unit cost of administering the bait. As the bait is still being researched, unit costs of mass administration are not available. For the purpose of this analysis, oral rabies vaccination costs were used as a proxy. Between 1995 and 2006, an oral rabies vaccination campaign was performed in 20 counties in South Texas to combat canine and fox rabies. The campaign led to the elimination of canine variant rabies with a unit bait administration cost $2.87 [73].

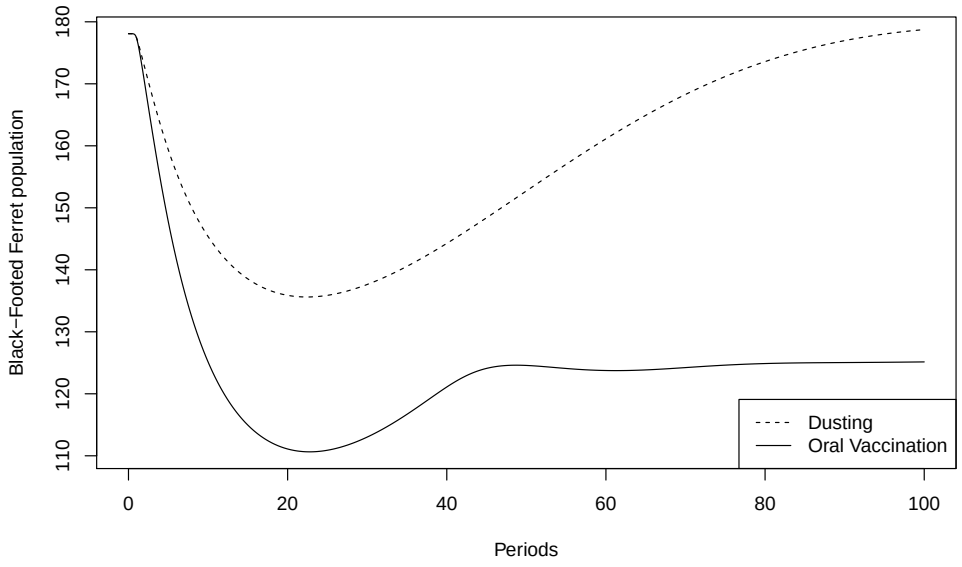

FIGURE 2.2. Black-footed ferret population dynamics under dusting and oral vaccination strategies when constrained by the maximum available budget.

Table 2.2 provides the estimated results for a 100 year simulation.

TABLE 2.2. The effort, steady state (SS) black-footed ferret populations, and associated total biomass that each hypothetical fixed budget affords

	Dusting			Oral Vaccination		
Budget	**Effort**	**SS**	**Biomass**	**Effort**	**SS**	**Biomass**
\$6,103	0.1	7	13,288	2,127	39	36,557
\$12,206	0.2	9	16,831	4,253	57	55,417
\$18,309	0.3	12	20,972	6,380	70	69,533
\$24,412	0.4	14	25,940	8,506	81	80,987
\$30,516	0.5	17	32,103	10,633	90	90,675
\$36,619	0.6	22	40,334	12,759	98	99,066
\$42,722	0.7	31	52,658	14,886	106	106,462
\$48,825	0.8	50	74,216	17,012	113	113,055
\$54,928	0.9	99	121,152	19,139	119	118,990
\$61,031	1	179	179,206	21,265	125	124,364

2.3.3. INPUT REQUIREMENTS FOR TARGET POPULATION OUTCOME. Now, rather than a manager seeking the best outcome given a fixed budget, assume that the manager is given a target black-footed ferret population outcome. The manager is interested in understanding the costs required under dusting and oral vaccination scenarios to achieve the desired outcome. The maximum possible outcome is achieved when dusting effort, $e_d = 1$, or when the manager applies coverage to 100% of the available colony area in each period. This means that all animals are constantly covered at all times. In contrast, given the exponential nature of the baiting success function, the vaccination rate will approach 100% but will not reach it, regardless of the chosen λ (figure 2.1). For this reason, oral vaccination will never provide a larger steady state ferret population then dusting, though given a high enough bait density, the difference will be negligible.

Using a dusting effort of 100%, the maximum possible steady state ferret population can be identified as $N_{BFF}^{max} = 179$. Further, the minimum desirable population is assumed to be $N_{BFF}^{min} = 50$. We identify 10 potential target ferret steady state populations between the desired minimum and maximum and find the required inputs in the form of dusting and oral vaccination effort to achieve the targets (Table 2.3). Figure 2.3 illustrates the same

ferret population dynamics when the target steady state population is $N_{BFF}^{max} = 179$. This requires a dusting effort of $e_d = 1$ meaning that 100% of the landscape is protected, and a oral vaccination effort of $e_v = 49{,}880$, meaning that 49,880 baits are distributed across the landscape.

TABLE 2.3. The effort required to achieve a specific fixed black-footed ferret steady state population with the associated cost and biomass

	Dusting			Oral Vaccination		
Target SS	**Effort**	**Biomass**	**Cost**	**Effort**	**Biomass**	**Cost**
50	0.8	74,216	$48,825	3,290	47,688	$9,442
64	0.842	88,999	$51,388	5,330	62,981	$15,297
79	0.872	103,332	$53,219	8,090	78,905	$23,218
93	0.892	115,496	$54,440	11,250	93,227	$32,288
107	0.908	127,373	$55,416	15,040	106,965	$43,165
122	0.922	139,966	$56,271	19,930	121,050	$57,199
136	0.934	153,060	$57,003	25,390	133,474	$72,869
150	0.942	163,310	$57,491	31,880	145,002	$91,496
165	0.95	174,622	$57,979	41,260	157,141	$118,416
179	0.956	178,996	$58,346	49,880	163,913	$143,156

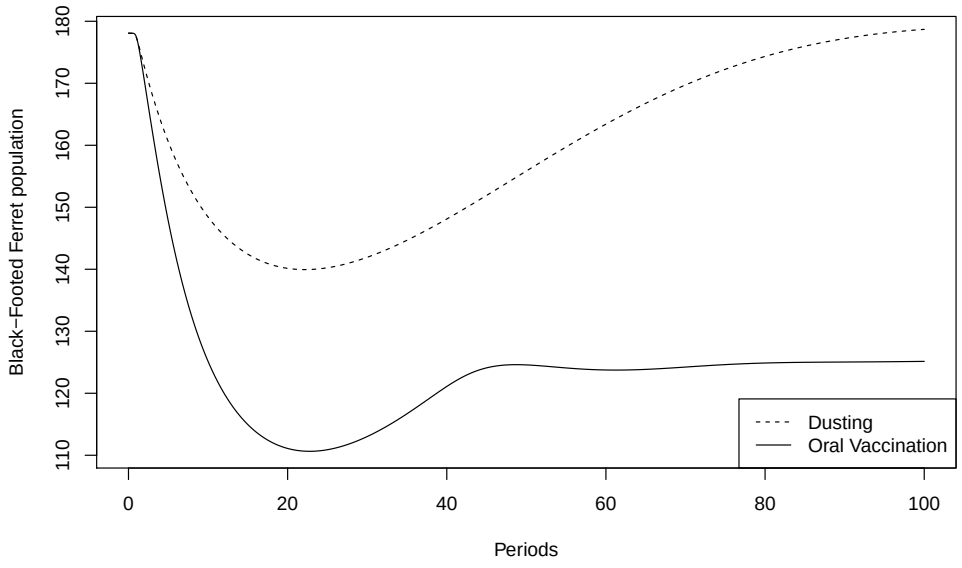

FIGURE 2.3. Black-footed ferret population dynamics using the required dusting and oral vaccination efforts when the target population the maximum possible

The results illustrate that there exists a threshold steady state ferret population at which the most cost effective strategy switches from oral vaccination to dusting. Below the threshold population, oral vaccination provides the target outcome at a lower cost, and after the threshold, dusting becomes more effective. Dusting provides little overall protection at lower effort levels but increases in effectiveness exponentially. Oral vaccination provides larger marginal gains at lower effort levels but exhibits diminishing returns. Oral vaccination theoretically, cannot provide 100% coverage but asymptotes at the full coverage level. Figure 2.4 illustrates this relationship using the assumed parameter values. The threshold occurs at a ferret population outcome of roughly 122 animals. At the point where the curves cross, the manager would be indifferent between dusting and oral vaccination as both strategies would produce the same result for the same price. This particular threshold is a product of the parameters used, especially values used for λ and the unit bait cost, which are both assumed. As an example of how the results might change, figure 2.4 also presents a scenario where $\lambda = 0.8$. In this case, the threshold occurs at a ferret population outcome of roughly 108 animals. In the next section the sensitivity of this threshold to values for λ and bait cost will be explored more fully.

2.3.4. Parameter sensitivity. As is true with all biological and economic modeling, functional forms and parameter values are likely to vary between circumstances and contexts. A sensitivity analysis is then performed to determine how the outcomes change as the values of specific parameters change. This analysis includes many parameters, all of which could be examined to determine the outcome's sensitivity to changes, however, many parameters are assumed to be accurate or relatively unimportant. Also, an examination of all parameter values would produce many possible outcomes, too many to present in this paper, therefore,

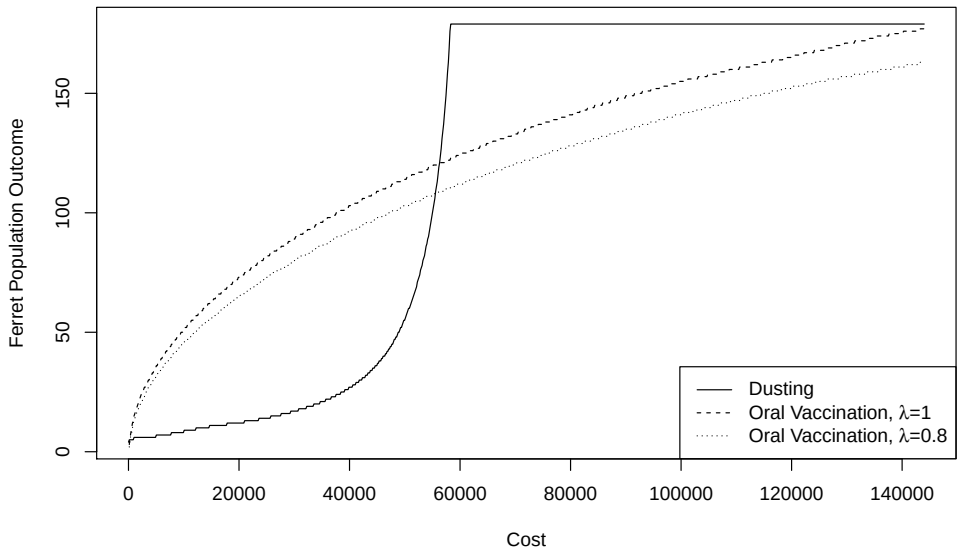

FIGURE 2.4. The costs of achieving specific ferret population outcomes and the threshold at which dusting becomes the more cost effective management strategy

only a handful of parameters are considered.

The parameters chosen all lack empirical results from which estimates could be taken requiring arbitrary assumptions to be made. The first is the contact parameter ϵ, in the disease transmission function, equation 2.8. This parameter determines the degree of density dependence in the transmission of plague from one animal to another. The second parameter is the migration parameter η, in equation 2.9, which determines how quickly ferret populations move between protected and non-protected areas of the landscape when density differs. Finally, baiting success λ, which influences the probability of baiting success, and the unit bait cost cV , are considered. All of these parameters will influence the threshold ferret population at which cost effectiveness will switch between oral vaccination and dusting, as well as the potential steady state populations and the aggregate biomass achieved. Changes in λ and c_V will influence the shape of the oral vaccination curve, thus changing the point

at which the dusting and oral vaccination curves cross. Changes in η will influence the over all level of management necessary to control the disease, and ϵ will influence the shape of the dusting curve.

All of these parameters will influence the threshold ferret population at which cost effectiveness will switch between oral vaccination and dusting, as well as the potential steady state populations and the aggregate biomass achieved. Changes in λ and c_V will influence the shape of the oral vaccination curve, thus changing the point at which the dusting and oral vaccination curves cross. This can be visualized in figure 2.4. Changes in η will influence the overall level of management necessary to control the disease, and ϵ will influence the shape of the dusting curve.

Figures 2.5 illustrate the sensitivity of the threshold to variations of the values for each of the parameters. Tables 2.4 and 2.5 provide estimates on the change in steady state ferret populations and aggregate biomass for assumed low and high estimates of each parameter.

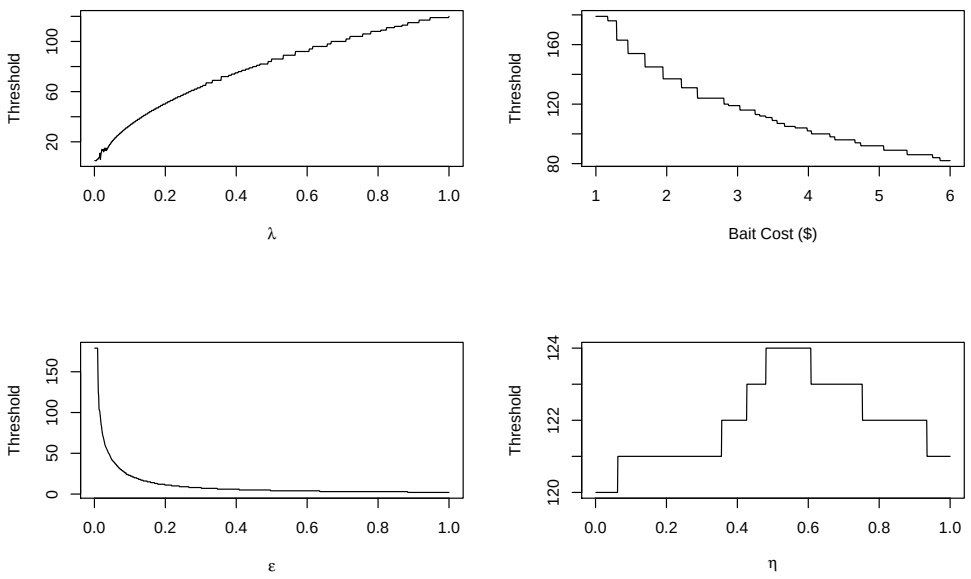

FIGURE 2.5. Holding all else constant, the ferret population threshold given values of λ, the bait cost, ϵ, and η

TABLE 2.4. Sensitivity of parameters related to dusting

	Baseline		**ϵ=0.008**		**ϵ=0.012**		**η=0.1**		**η=0.3**	
Budget	**SS**	**Biomass**	**SS**	**Biomass**	**SS**	**Biomass**	**SS**	**Biomass**	**SS**	**Biomass**
\$6,103	7	13,288	9	14,575	6	12,340	7	13,659	7	12,943
\$12,206	9	16,831	12	18,872	8	15,405	10	17,188	9	16,496
\$18,309	12	20,972	15	23,804	10	19,022	12	21,343	12	20,622
\$24,412	14	25,940	17	29,659	12	23,391	14	26,336	14	25,565
\$30,516	17	32,103	22	36,853	14	28,843	17	32,544	17	31,688
\$36,619	22	40,334	28	46,371	19	36,173	23	40,882	22	39,828
\$42,722	31	52,658	39	60,466	26	47,235	32	53,478	31	51,930
\$48,825	50	74,216	60	84,691	42	66,840	51	75,811	49	72,894
\$54,928	99	121,152	116	136,134	86	110,410	102	124,570	96	118,695
\$61,031	179	179,206	179	179,206	179	179,206	179	179,206	179	179,206

TABLE 2.5. Sensitivity of parameters related to oral vaccination

	Baseline		**λ=0.8**		**Bait Cost=\$1.50**		**Bait Cost=\$3.50**		**ϵ=0.008**		**ϵ=0.012**	
Budget	**SS**	**Biomass**	**SS**	**Biomass**	**SS**	**Biomass**	**SS**	**Biomass**	**SS**	**Biomass**	**SS**	**Biomass**
\$6,103	39	36,557	35	31,753	55	54,020	31	27,422	45	42,754	36	32,063
\$12,206	57	55,417	50	48,648	79	79,144	45	42,459	64	63,920	51	49,121
\$18,309	70	69,533	62	61,472	96	96,989	55	54,020	78	79,645	63	61,957
\$24,412	81	80,987	72	71,997	111	110,851	64	63,604	90	92,361	73	72,394
\$30,516	90	90,675	81	80,989	123	122,099	72	71,861	101	103,097	82	81,228
\$36,619	98	99,066	88	88,989	133	131,455	79	79,144	111	112,388	89	88,877
\$42,722	106	106,462	95	95,843	143	139,345	85	85,673	119	120,574	96	95,616
\$48,825	113	113,055	102	102,131	151	146,028	91	91,584	127	127,867	102	101,616
\$54,928	119	118,990	107	107,840	158	151,702	96	96,989	134	134,425	108	107,011
\$61,031	125	124,364	113	113,055	164	156,527	101	101,963	141	140,347	113	111,891

2.4. Discussion

The purpose of this paper is to show that population management requires an understanding of the inter-species ecology as well as the effect of management strategies on the disease dynamics. We focus on how disease management mitigation strategies influence interspecific wildlife dynamics. We also explore the differences between spatial disease protection and individual disease protection when elimination is not attainable and reduced populations are not desirable.

This is a contribution to the literature in that no other study of black-footed ferret management previously considered the cross species dynamics when determining which management strategies to pursue. Most attempts to understand the relationship between effort and biological outcomes were overly simplistic and did not adequately address the spatial, temporal, and interspecific dynamics. We present a much more complex model that accounts for all of these dynamics, providing a much more complete picture of cause and effect. We believe that the complexity of our model is necessary as simplifying any further would lead to loss of realistic dynamics. Previously, the most useful understandings of how management efforts related to program success have been gathered from trial and error or simple case studies. We hope to provide better insight before programs start in order to guide program strategy.

While preserving highly endangered species is important, it is also vital to understand the limits of management efforts and strategies to identify optimal strategies in terms of cost effectiveness given various program goals. In some cases, managers may significantly overspend simply to ensure a beneficial outcome without the understanding of the marginal costs of those benefits. We outline those marginal benefits and marginal costs in this paper

allowing for managers to achieve the desired results while spending the minimum necessary amount. Goals such as maximizing abundance, achieving a target abundance at the lowest possible cost or providing insight into optimal strategies when facing budget constraints.

We show the relative values of spatial disease protection and individual disease protection. From a human perspective, this can be viewed as the value of maintaining a border, or preventing the outbreak of disease vs. the value of protecting individuals through vaccination or other methods.

We find that there exists a threshold target population level, below which, oral vaccination (individual protection) is more cost effective, and beyond which dusting (spatial protection) is more cost effective. This result comes from the functional forms of the protection equations. Given that movement between spatially protected and non protected areas can occur, the largest marginal benefits from dusting occur at higher levels of overall landscape coverage. This is an important result that can guide future management decisions in the face of budget constraints or specific abundance goals. For example, if a manager if facing a fixed budget, the size of the budget will determine whether dusting or oral vaccination efforts should be pursued to maximize the benefits. Likewise, a desired abundance will determine the most cost effective approach to achieving that abundance.

For oral vaccination, the marginal benefits of effort are increasing but at a decreasing rate. This is due to the fact that full coverage of the population is theoretically not possible. Coverage will approach, but will not achieve, 100%. The opposite if true for spatial protection. Benefits grow exponentially eventually achieving 100% protections, beyond which, any additional effort is wasted with zero marginal benefit. While these results are specific to the case of black-footed ferret population management, the general result likely holds in other

cases when considering spatial vs. individual disease protection strategies. For humans, it would be the difference between maintaining disease free areas through strict border control, and no border control with individual disease vaccination efforts.

These results should not be interpreted as globally optimal strategies as global solutions were not derived due to the complex nature of the model. The results reflect possible management decisions given potentially fixed budgets or target populations.

Essay #3: BioEcon: An individual-based, stochastic simulation model for wildlife population and disease management with an application to canine rabies

3.1. Introduction

The spread of infectious disease from wildlife to domesticated animals is a major worldwide problem. Wildlife related diseases that spread to livestock, for example, have the potential to cost billion of dollars. The USDA has estimated that a Foot-and-Mouth Disease (FMD) outbreak in the UK in 2001 cost $13 billion and reduced the UK economy by 0.3%, and that a similar outbreak in the US (which is considered FMD free), could cost billions in first year alone, plus the ongoing costs of losses, control, and management [35]. Beyond the initial and ongoing losses, costs occur in the form of increased trade restrictions, and biosecurity measures. In 2000, Michigan lost its accredited Bovine Tuburculosis free status, which cost an estimated $22 to $74 million in the proceeding five years in the form of more stringent regulation and cattle losses [36]. [37] provide a table of 26 wildlife diseases that pose a risk to livestock as well as humans.

Wildlife managers are often tasked with reducing the abundance of a population or the disease prevalence within a population. Abundance may be managed to mitigate a negative impact such as crop damage or livestock predation, while disease prevalence may be managed due to concerns about its impact on wildlife, domestic animals, or human health. Management might also be motivated by multiple considerations and require balancing different objectives. In many settings, the strategic options available to managers can be quite diverse. Sport hunting, professional removal, permanent sterilization, and temporary contraception might be used to control abundance. Although disease prevalence can also be

managed indirectly by these same methods, in some cases it can be managed more directly with vaccination. Managers strategic choice problem is further complicated by the consideration of mixed strategies and strategies that vary temporally, spatially, and demographically.

The KwaZuluNatal (KZN) province of South Africa has had an ongoing programme for control of enzootic canine rabies since the late 1970s [74]. This province is the second most populated province of South Africa with more than 10 million residents and is located in the south-east portion of the country along the coast. There were 473 confirmed animal rabies cases, with six reported human deaths related to rabies in the project area when the programme was augmented in 2007. The dog vaccination campaigns have intensified since 2007, with the appointment of a provincial coordinator and single point of reference for rabies control, and since 2009, when the project, together with two others (in Tanzania and the Philippines), became demonstration sites supported by the Bill and Melinda Gates Foundation. Our objective was to estimate the cost and biological outcome of various vaccination strategies. A health economic data assessment such as we present here is a crucial component of disease control. This analysis can guide management decisions by highlighting cost-effective strategies. At a broader level, it will provide information to policy makers and other stakeholders regarding both the feasibility and public health benefits, stemming from reduced canine to human transmission, of the elimination of canine rabies. It is important to understand cost-effectiveness, which varies by region to allocate resources where they are most productive and stretch the furthest. To achieve our goal in this paper, model selection was crucial to accurately estimated outcomes in a highly stochastic environment with regionally specific parameters.

In an attempt to identify the appropriate model to use to ultimately provide guidance for managers, we found that two types of modeling efforts are common. One approach considers the impacts of different management strategies by pairing a relatively complex model of biological dynamics (i.e. models with spatial, demographic, or social structure) with simple concepts of management (e.g. [75], [76], [39], [77]). For example, a Leslie matrix model or stochastic simulation model could be used to understand dynamics under alternative levels of removal, sterilization, or contraception within the population without consideration of the effort and costs that are required to achieve those levels. For a manager seeking strategic guidance, the failure of these types of models to consider effort and costs is problematic because different strategies require different levels of effort and entail different costs. Given that managers usually face budget constraints, accounting for the links between effort, costs, and biological outcomes is critical to understanding what strategies are feasible or to what extent specific strategies can be pursued.

In contrast, a second approach, often seen in the economics literature, incorporates the concepts of effort, cost, and catch into relatively simple models of biological dynamics and pairs the resulting bioeconomic models with sophisticated optimization techniques (e.g. [78], [79], [37], [80]). The relative simplicity of the biological models in these approaches is driven by the focus on identifying a globally optimal strategy and the resulting mathematical and/or computational burden imposed by the optimization method (e.g. optimal control, dynamic programming). Additionally, these models do not often assume an objective in terms of abundance or disease prevalence, but instead assume a manager attempts to maximize the net benefit of management to society. Thus, the focus is not limited to the optimal strategy

to achieve a certain abundance or disease prevalence target, but also includes the optimal abundance or disease prevalence at each point in time.

In any applied setting, there is certainly value in accounting for effort and costs and identifying optimal strategies. However, in many applied settings, the focus on comprehensive optimality present in many bioeconomic models is unlikely to be useful for several reasons. First, it comes at the cost of biological and strategic sophistication. For example, a model with little (or no) demographic or spatial structure cannot effectively account for strategies that vary by age, sex, or location. Additionally, if strategies alter demographic or spatial structure of the population, such changes likely affect biological dynamics. Second, managers face not only budgetary constraints, but also political and technical constraints. Thus, the manager may be choosing among a relatively small set of strategies that are deemed intuitively, politically, and technically feasible. Furthermore, management objectives are often influenced by politics and public opinion.

Although the two common approaches discussed above are often unable to provide specific strategic prescriptions, they remain valuable because they provide general lessons. Models that do not effectively account for effort and costs still provide valuable insight into the relative effectiveness of different types of management. Conventional bioeconomic optimization models assist managers in understanding the general characteristics of optimal strategies and provide insight into what those strategies depend on. However, in light of the above discussion, we propose a bioeconomic model (BioEcon) that strikes a balance between biological sophistication and the ability to identify optimal strategies while recognizing management resource constraints.

The bioeconomic model we ultimately propose to help answer our initial question is an individual-based stochastic simulation model that explicitly accounts for the links between effort, cost, and biological outcomes. Additionally, the model we propose goes beyond our initial question by allowing for general use across species and locations. The model we construct, (1) accounts for population and disease dynamics, (2) allows for removal, permanent sterilization, temporary contraception, and vaccination, (3) allows for strategies to vary temporally, spatially, and demographically, (4) allows for mixed strategies, (5) accommodates various levels of data availability, and (6) is flexible enough to allow parameterization and functional forms for a variety of wildlife species and diseases. The appendix provides a detailed description of the model and the rationale for its various mechanisms.

3.2. Parameterization for KwaZulu-Natal

3.2.1. Case Study Overview. The objective of this paper is not to provide a detailed examination of all potential alternative strategies for managing rabies in a free-ranging dog population. Given the scope of this paper, it is not feasible to fully examine the multitude of strategic possibilities and alternative parameter values that exist. Rather, our intention is to explore several potential vaccination strategies to illustrate the biological outcome over the different effort levels to ideally help identify a more optimal strategy given programme objectives. This will involve analyzing how abundance and disease prevalence change given various levels of vaccination effort and the associated costs. For example, if a manager prioritizes animal abundance above reduced disease prevalence, the optimal strategy may be different than if reduced disease prevalence is the priority. Also, given a likely fixed budget, what does the optimal strategy look like.

The modeling effort will take place on a 3x3 spatial grid where each cell is a distinct geographic location. We assume that each cell is 100 km^2. For simplicity in this paper, we assume that each cell has the same parameter values and will receive the same vaccination effort. The fact that free migration is allowed to occur will allow for varied outcomes by location. We assume that our modeled locations do not exist in isolation and that there exists an exogenous un-modeled disease threat. For example, from other South African provinces that may not currently have disease eradication programmes in place. We assume that migration cannot occur between these location, but that there exists a constant probability that disease can cross into our modeled area.

3.2.2. Population Model. We assume each of the nine cells is 100 km^2 and that carrying capacity is 10 dogs/km^2 based on [81–83], which also assume free-ranging dog populations in sub-Saharan Africa grow according to

$$\dot{N} = rN(1 - \frac{N}{K}) \tag{3.1}$$

where N is the canine population at any given point in time, r is the population growth rate, and K is the assumed population carrying capacity.

The assumption of logistic growth can be decomposed into a density-independent recruitment rate and a density-dependent mortality rate as

$$\dot{N} = N[a - (b + r\frac{N}{K})] \tag{3.2}$$

where a is the per capita recruitment rate, b is per capita mortality rate at low densities, and $a - b = r$. Following [82] and [81], we assume $b = 0.33$ year [5]. For use in this model, the annual rate must be converted to daily probabilities. An annual per capita mortality rate of $0.33 + 0.09(N/K)$ implies a daily mortality probability of

$$1 - e^{\frac{-0.33-0.09(N/K)}{365}} \tag{3.3}$$

[81] assumed an annual birth rate of 0.42. This yields an annual probability of $1-exp(-0.42)$. However, the model that relied on the birth rate of 0.42/year did not distinguish between males and females or juveniles and adults. Thus, the expected number of births per day is simply $N[1-exp(-0.42/365)]$. Our model, however, requires a daily probability of successful mating for each adult female that is fertile. We assume a mean litter size of 4.7 and a disease-free population that is 40% female [84], Furthermore, trial simulations imply that about 67% of the population is sexually mature. We then can assign a daily probability for mating by writing

$$0.93[N(0.4)(0.67)Prob(mating)]4.7 \cong N[1 - e^{\frac{-0.42}{365}}] \tag{3.4}$$

where 0.93 reflects the probability that a females survives the gestation period. Solving equation 3.4 yields a daily probability of successful mating by a sexually mature female of 0.00094.

[5] note that these rates reflect changes in density rather than abundance

Gestation duration is set at 63 days [85], dispersal of puppies from mothers at 13 weeks [85], and puberty at 10 months [86]. Finally we assume that 40% of puppies are female [84][6].

3.2.3. Disease Model. We follow [82, 81] and assume density-dependent transmission of the form βSI. [81] estimates a transmission coefficient (β) of 13.2. The variable S is the number of susceptible animals with I being the number of infected animals. This coefficient and the assumption of density-dependent transmission imply a daily probability of transmission of approximately

$$1 - e^{-\left(\frac{13.2}{365}\frac{I}{100}\right)} \tag{3.5}$$

where I is the number of dogs in the infectious stage of the disease at any point in time. Time spent in the exposed state E, and infected state I, are based on estimates by [81] and are set at 25 days and 6 days respectively, so that for simplicity we assume non stochastic transition times between disease stages. We also assume that the disease is 100% fatal, so there is no recovery stage.

3.2.4. Management. We explore several potential vaccination management strategies in order to compare the subsequent biological outcomes associated with each. The first strategy is no management of any kind with no disease. In this scenario we start each of the nine locations with a population abundance at carrying capacity. All simulations are run for 20 years. This will provide a benchmark against which disease impacts can be compared. The second is equal to the first except that an exogenous disease threat will be introduced at

[6]The sex ratio of living dogs reported by [84] may not be representative of the sex ratio of living dogs at birth, but we assume 40% of births are female because we do not specify sex-specific mortality probabilities. [85] reports 37% of births are female, which lends further support to our assumption

day one which continues throughout the simulation. This scenario will provide a benchmark against which management benefits can be compared. The third and subsequent scenarios are equal to the second but will also involve various levels of disease intervention through vaccination.

For management, we will assumed a trap density ranging from one trap every 200 km^2 to one trap every 10 km^2. All animals captured will be vaccinated for disease control. We assume that traps are checked daily so that the traps can capture new animals (or potentially, the same animals) daily. Animals have an assumed daily probability of encountering a trap of 0.0025 per trap, and of being trapped [7]. Animals may be trapped any number of times, though we do not assumed any trap shyness or preference so that the probability remains the same regardless of the number of times an animal has been trapped.

Vaccination is assumed to be effective for three years. The manager then, will only re-vaccinate a previously vaccinated animal is they were vaccinated longer than three years previously. We also assume that a manager knows if an animal is currently vaccinated if it is captured multiple times, meaning that animals can be effectively marked after vaccination.

We assume that the cost of setting or checking a trap is \$20 per day, per trap. We also assume that each trap is checked daily and that the chosen management strategy is administered. In our case, vaccination of any un-vaccinated animal. We assume the cost of vaccination to be \$3 per animal, in addition to the cost of trapping the animal. So then for example, if a manager captures a recently vaccinated animal that does not need an additional vaccination, the manager releases the animals sans vaccination, saving \$3, but still incurs the cost of checking the trap of \$20.

[7] We assume that if an animal encounters a trap, they will be captured

3.2.5. Simulation. We run a total of 24 simulations. The first simulation starts each location with a relatively low abundance which is allowed to grow unmanaged for the duration of the simulation. This is to illustrate the growth dynamics of the population. The second simulation starts with a population at carrying capacity in location one only. The population is then allowed to immigrate to all other locations, and grow. This is to illustrate immigration dynamics of the population. Only one iteration is performed for these two simulations to illustrate the inherent randomness in the model. For all subsequent simulations for which insight will be extracted, 100 iterations are performed with the mean values presented.

We then move onto the disease and management scenarios. Simulations 3-24 provide insight into the potential impact of an unmanaged disease on a healthy population and the potential benefits and costs of intervention strategies. We explore 20 intervention scenarios ranging from effort levels of 0.5 traps placed per 100 km^2 to 10 traps per 100 km^2 per day. All simulations are run for 20 years and outcomes are averaged over 100 iterations. This takes roughly one hour per scenario.

3.3. Results

3.3.1. Dynamics without Disease. We begin by examining population dynamics without disease. To illustrate growth from a sub carrying capacity level of abundance we allow the population to grow from an initial population of 600 animals per location to carrying capacity (Figure 3.1). We can see that location five reaches carrying capacity relatively quickly given that migration is possible from all surrounding locations leading to a larger influx of animals than in any of the other locations with fewer potential migration destinations.

This leads to a population that is generally higher than carrying capacity, and therefore, a higher mortality rate.

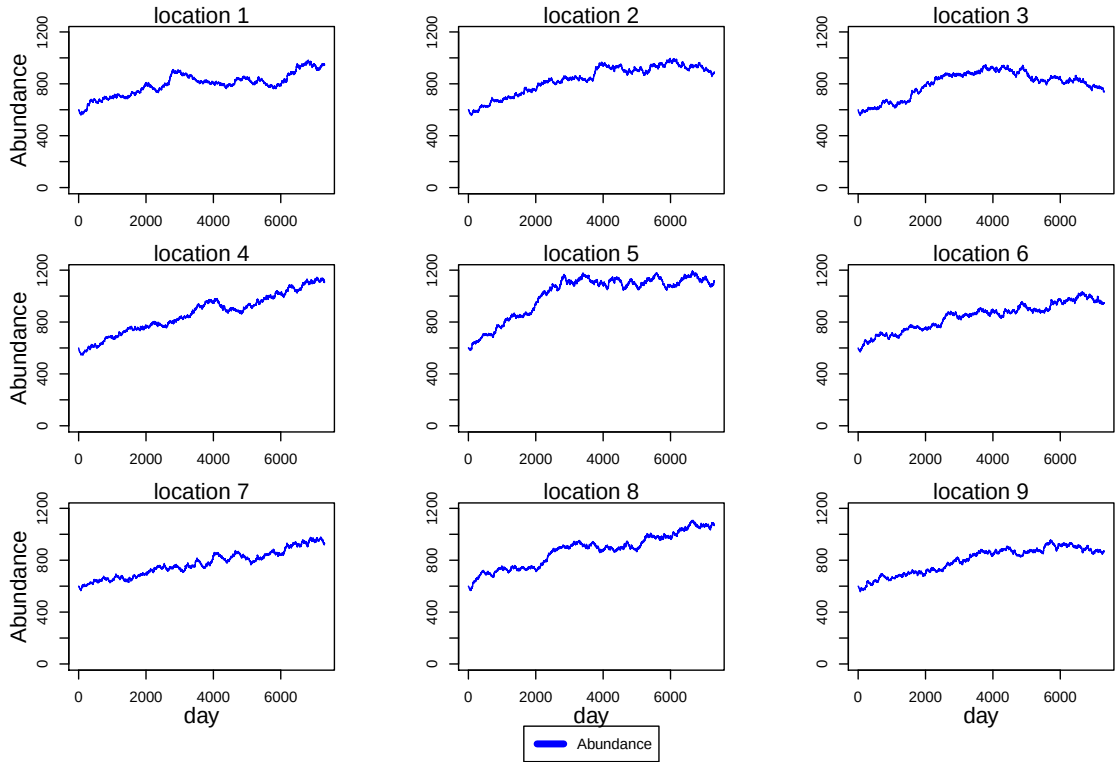

FIGURE 3.1. Population growth dynamics from a relatively low abundance over 20 years

We also illustrate immigration between areas by starting a simulation with a population of dogs at carrying capacity in area one only and allowing that population to move between locations over the 20 year period. (Figure 3.2). Here we see the population of location one decline. Only at year 20 does the population again reach carrying capacity. This is because as surrounding migration destinations become more populated, there is less incentive to move locations. And also, because animals begin to migrate back to location one. It is interesting to note that even after 20 years, locations 3, 6, and 9 are still relatively uninhabited.

Finally, we establish a baseline population in each location by starting a simulation with abundance at carrying capacity which is left unmanaged for 20 years (Figure 3.3). Disease

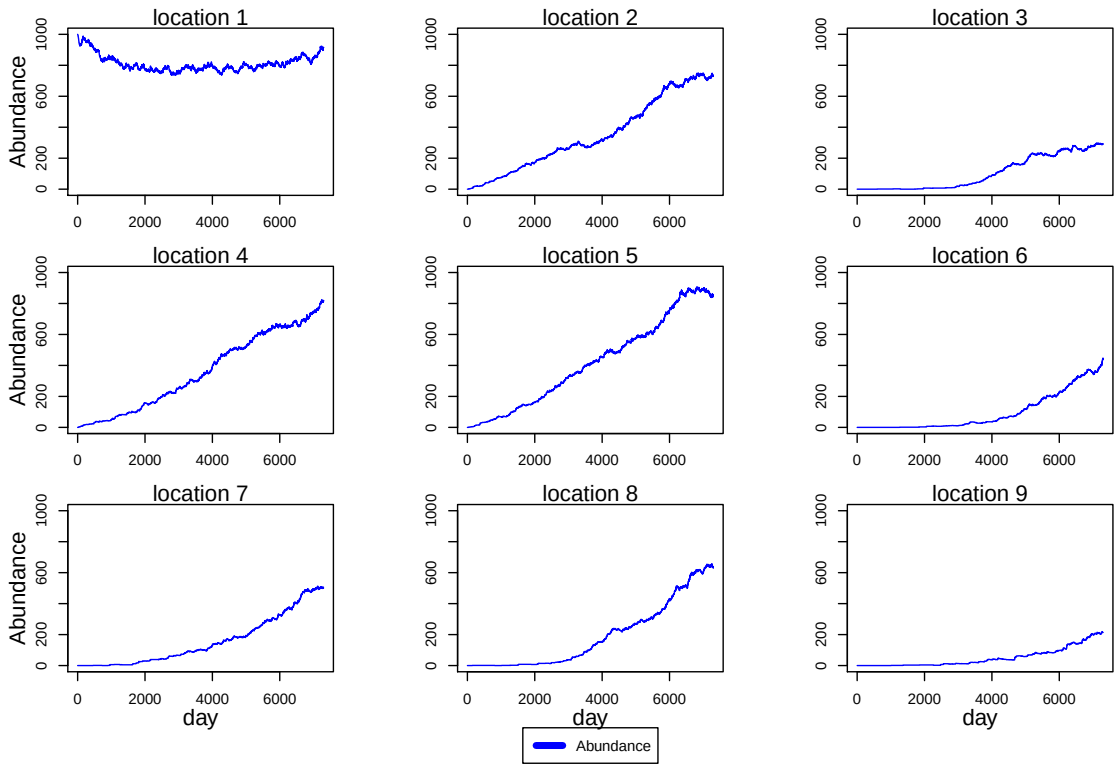

FIGURE 3.2. Random immigration from location one to all other locations over 20 years

prevalence is zero as no disease is introduced. This will allow us to understand the benefits of no disease as well as the cost of having the disease present.

3.3.2. DISEASE DYNAMICS WITHOUT MANAGEMENT. To illustrate the effects of disease on the population, we simulate a healthy population which is exposed to the disease via constant exogenous risk from outside non-managed areas. The exogenous threat only threatens the outer areas, though the disease can spread to the center area via animal migration. We assume an annual exposure probability of 0.05% (Figure 3.4).

We see a very large drop in the population associated with a large initial outbreak of the disease. This is due to the density dependent nature of the disease which spreads quickly in dense populations. Subsequent outbreaks are smaller given the lower overall abundance. We see that the disease keeps the population at a steady level creating an "equilibrium"

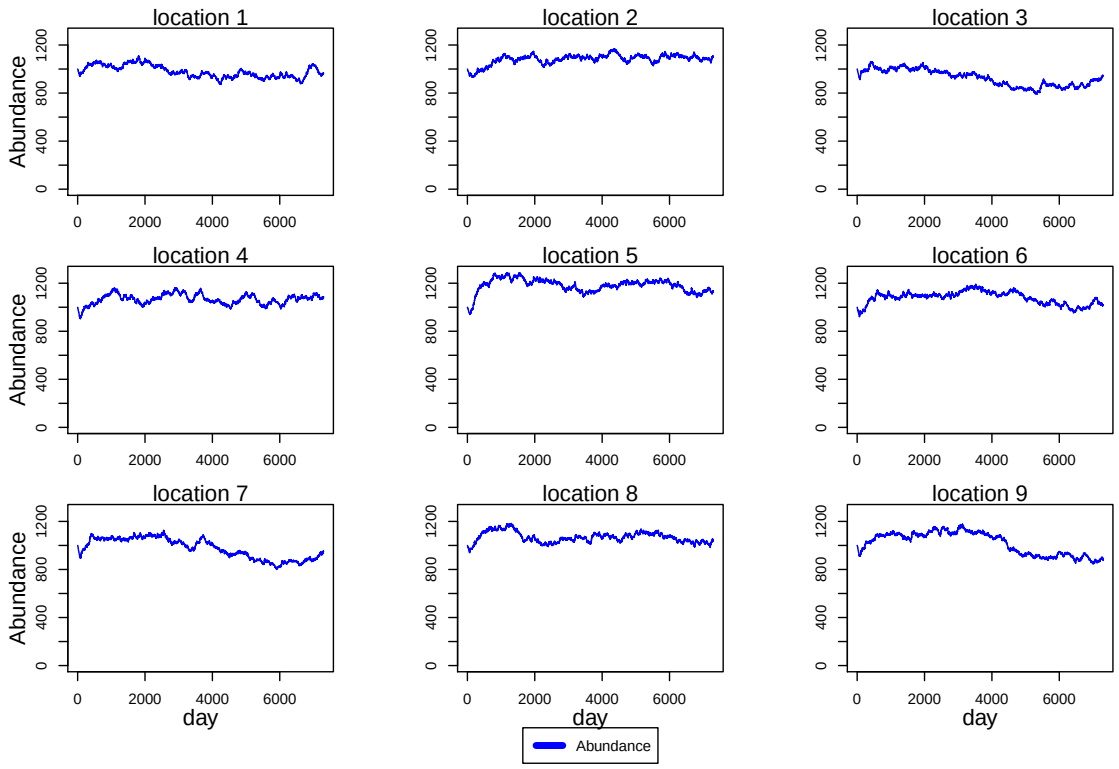

FIGURE 3.3. Unmanaged population dynamics over a 20 year simulation. These results will be used as a baseline against which disease intervention outcomes can be compared.

population level and disease prevalence. This scenario will be used as the disease baseline. We can compare management strategies to this outcome to identify the potential benefits of effort.

3.3.3. COSTS OF MANAGEMENT AND RESULTING DYNAMICS. We explore the impact of different intervention effort levels in the form of the number of traps placed and managed per $100km^2$ area, and their subsequent benefits and costs. The benefits are assumed to come in the form of reduced number of infected animals at any given time and the increased number of healthy animals, depending on the desired objective. More indirect benefits include the potential benefits to humans in the form of fewer diseased animals, and thus, a lower probability for human exposure.

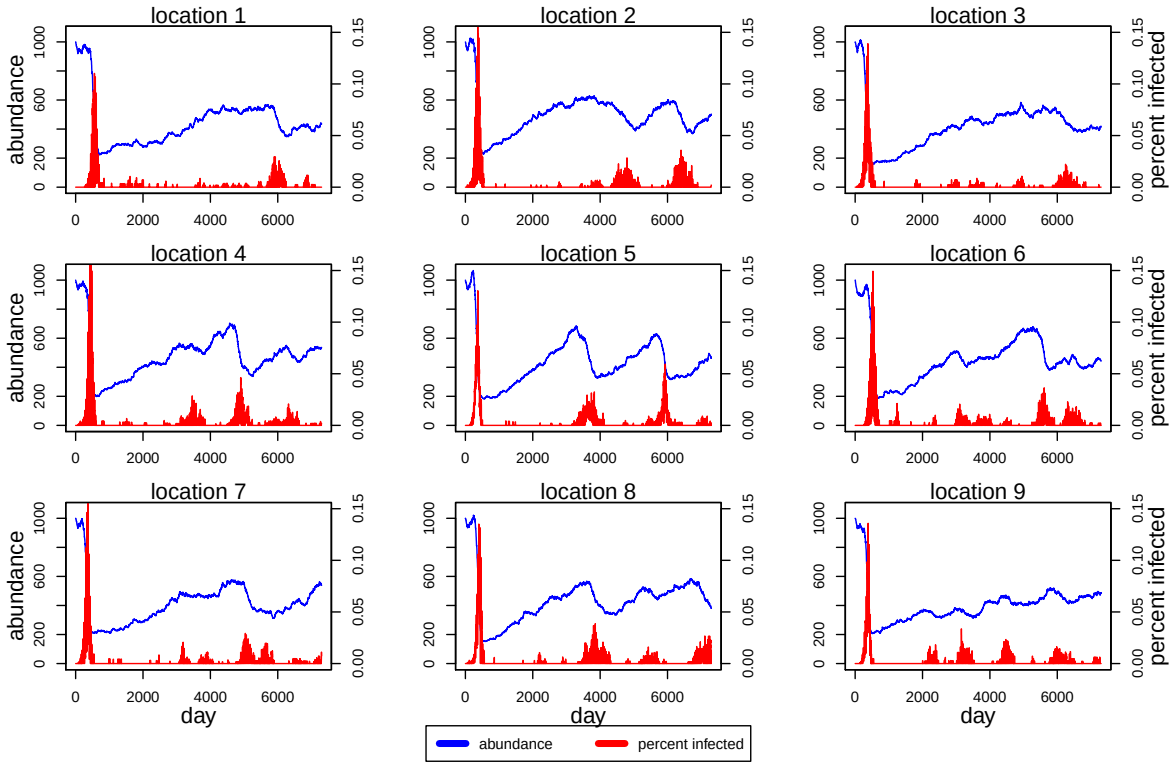

FIGURE 3.4. Dynamics under exogenous probability of exposure.

In order to compare the impact that each effort level has on population dynamics, we sum the overall biomass across all 20 years and all nine locations, and examine their associated costs of management. This will give us what we call "Health Dog Days", and "Diseased Dog Days", or simply, the number of health or diseased dogs at each location on each day, summed over the 20 years.

We begin with an effort level of 0.5 traps placed per $100km^2$ (Figure 3.5), and end with an effort level of 10 traps per $100km^2$ (Figure 3.6). We also run simulations for all effort levels in between at 0.5 increments.

One of the main benefits which can be seen from even low levels of effort in Figure 3.5 is the noticeable dampening of the initial disease outbreak. Comparing this to no intervention in Figure 3.4, we see a more gradual, though still rapid, disease spread leading to a low point population of almost 20% higher than what is seen in no intervention. Though the

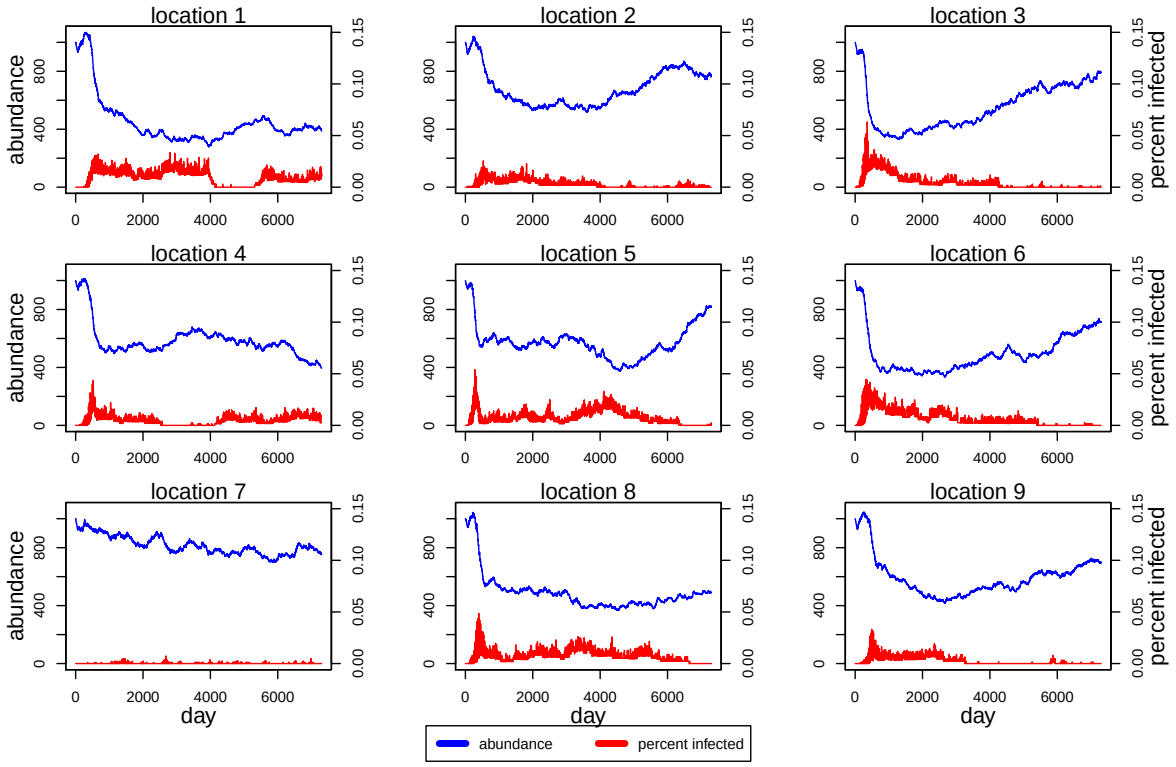

FIGURE 3.5. Dynamics under exogenous probability of exposure and a vaccination effort of 0.5 traps per $100km^2$.

population still declines by a large degree and "settles" at a point roughly 60% the disease free carrying capacity.

In the high effort scenario (Figure 3.6), there is an insignificant initial outbreak, only minor flair ups in each location, and a larger, though still relatively small, sustained diseased population in location 5 from roughly year 10 to the end of the simulation. Though, note the scale of the second Y axis in Figure 3.6. These are very small prevalence levels.

Table 3.1 illustrates the resulting total number of health dog days, diseased dog days, intervention costs, marginal costs, and marginal benefits of each subsequent effort level. The marginal cost is defined as the additional cost of moving from one effort level to another. The marginal benefit is defined as the change in the number of diseased dog days.

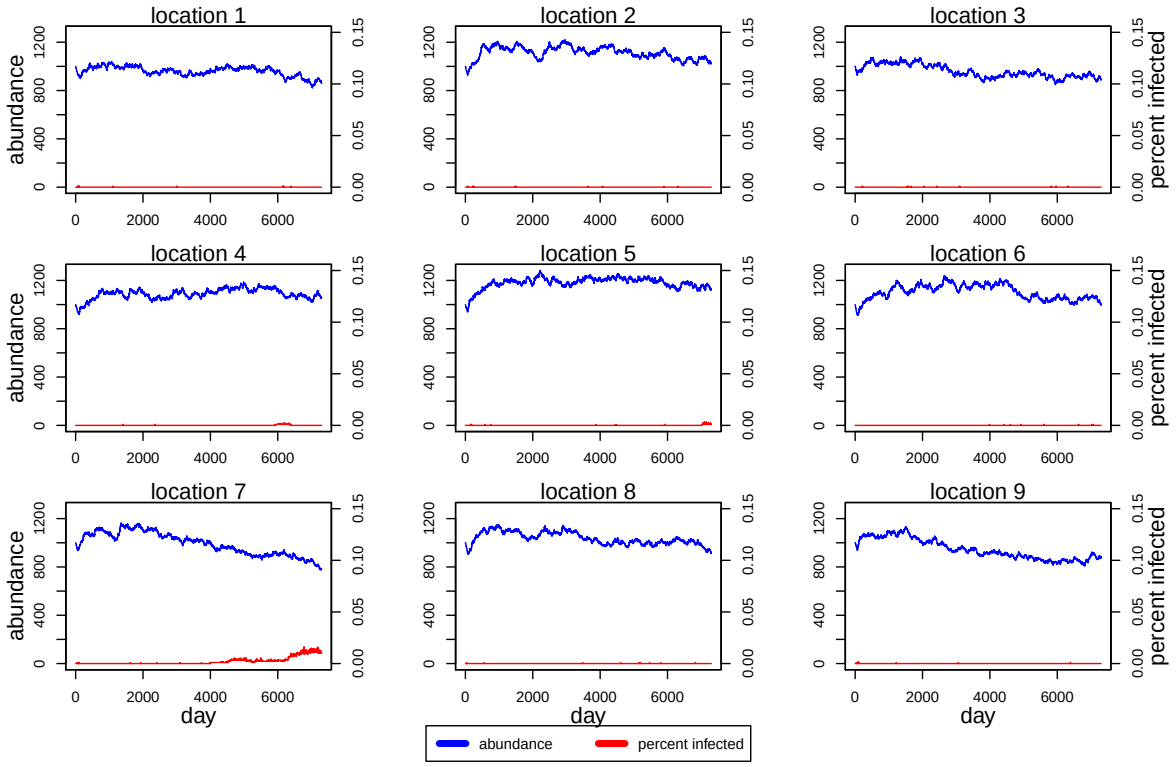

FIGURE 3.6. Dynamics under exogenous probability of exposure and a vaccination effort of 5 traps per $100km^2$.

TABLE 3.1. Resulting animal biomass and costs associated with various management strategies in the form number of traps sets per $10km^2$.

Scenario	**Healthy Dog Days**	**Diseased Dog Days**	**Cost**	**Marginal Cost**	**Marginal Benefit**
Baseline No Disease	67,634,378	0	$0	$0	0
Disease, No Effort	29,043,283	81,922	$0	$0	81,922
$0.5/100km^2$	36,995,769	190,337	$76,025	$76,025	108,415
$1/100km^2$	46,134,647	259,907	$133,255	$57,230	69,570
$1.5/100km^2$	53,213,330	267,208	$179,398	$46,143	7,301
$2/100km^2$	58,016,018	244,208	$213,825	$34,427	-23,001
$2.5/100km^2$	62,188,865	175,991	$243,564	$29,739	-68,217
$3/100km^2$	62,744,736	186,069	$255,474	$11,910	10,079
$3.5/100km^2$	64,549,535	148,230	$271,318	$15,844	-37,839
$4/100km^2$	65,436,989	116,350	$282,031	$10,713	-31,880
$4.5/100km^2$	65,991,975	98,299	$289,518	$7,487	-18,051
$5/100km^2$	66,182,293	86,687	$294,736	$5,218	-11,613
$5.5/100km^2$	66,473,146	90,747	$299,815	$5,079	4,060
$6/100km^2$	66,954,439	66,054	$305,354	$5,539	-24,692
$6.5/100km^2$	67,024,161	59,024	$308,038	$2,684	-7,030
$7/100km^2$	67,216,108	41,569	$311,975	$3,937	-17,455
$7.5/100km^2$	67,243,235	30,122	$313,704	$1,729	-11,447
$8/100km^2$	67,416,845	33,861	$316,691	$2,987	3,739
$8.5/100km^2$	67,481,740	27,497	$318,655	$1,964	-6,365
$9/100km^2$	67,511,653	20,132	$320,305	$1,651	-7,365
$9.5/100km^2$	67,665,873	21,340	$322,427	$2,122	1,208
$10/100km^2$	67,531,152	13,694	$322,747	$319	-7,646

It is interesting to note that initially, as effort increases, so does the number of diseased dog days (Figure 3.7). This is due to the increased population of healthy dogs stemming from even small amounts of disease protection. This increases the population density, so that when an outbreak occurs, it spreads rapidly. Only at an effort level of two traps per $100km^2$ do we start to see declining diseased dog days.

This provides for an interesting solution given an objective of minimizing disease prevalence. Given a large enough budget, the optimal solution would obviously be to simply vaccinate as many animals as possible which leads to lower levels of disease prevalence. But if the budget is sufficiently low, the optimal strategy would be to not manage the population at all. We see that under the no management scenario, the number of diseased dog days is 81,922. As effort increase, that number also increases until an effort level of two traps per $100km^2$, but does not reach the same number until an effort of between roughly five and six traps per $100km^2$. The associated cost being between roughly \$294,736 and \$305,354. So for a strategy of minimizing disease prevalence, effort is only optimal when it can exceed five to six traps per $100km^2$, otherwise, no effort should be expended.

If maximizing the healthy population is the objective, All levels of effort increase the benefit relative to a no effort scenario, though at a declining marginal rate.

3.3.4. Discussion and Conclusion. This paper outlines the costs and benefits of potential canine rabies vaccination strategies specific to a KwaZulu-Natal, South Africa context. We identify the conditions under which certain vaccination effort strategies would be optimal given specific management objectives. We also provide insight into the potential disease and population dynamics stemming from various effort levels. We show that from a

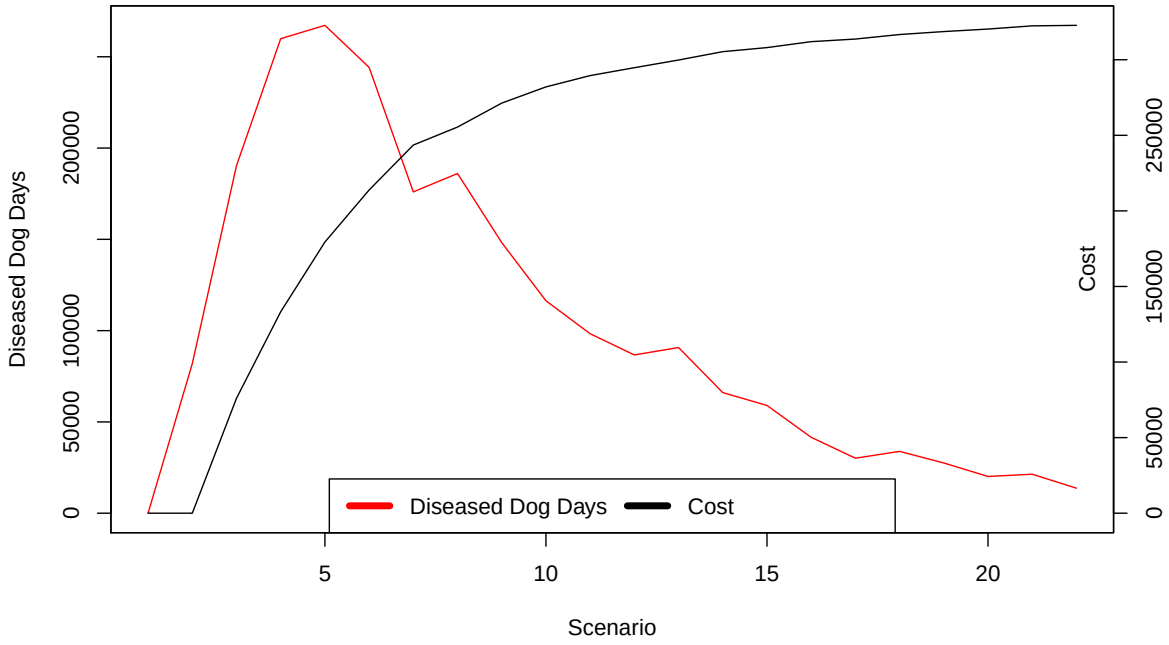

FIGURE 3.7. Cost and number of diseased dog days for each effort scenario.

no management scenario, increased effort will increase both healthy and diseased populations up to a certain effort threshold (1.5 traps per $100km^2$ in our case).

We also show that given a strategy of minimizing disease prevalence, there exists a minimum required investment in order to reduce prevalence below the baseline no management scenario. We find the minimum to be between roughly $294,736 and $305,354, as any investment less than this would actually increase disease prevalence by increasing the healthy dog population, and thus population density. This finding can likely be assumed to general across other locations and programmes. This is important as most vaccination campaigns are likely operating on limited or fixed annual budgets. If those budgets are consistently lower than the required minimum, disease prevalence may actually be increasing across the landscape. In these cases, it may be more beneficial to focus funds on a specif location within the programme area (location one in our case for example) in order to achieve the required

trap density to reduce disease prevalence within that area, and thus have reduced prevalence as a whole across the programme area.

These results may also be beneficial to managers who consistently face external threats of disease introduction and help to understand the benefit of maintaining an active "border". For this scenario, compare the scenario with no disease to a scenario where the disease is introduced via an exogenous threat. The cost of returning to a disease free status is likely much more than the cost of maintaining vigilant border disease screening.

We develop a model that has yet to exist for this specific application (and likely many others) but is needed. Traditionally, there has been little data or modeling available to allow for an analysis of an optimal strategy. Generally, understanding of how effort relates to biological outcomes has come from case studies of specific programmes. This usually allows for analyzing only one specific strategy in isolation. There is no ability to compare the outcome to other strategies. Beyond this, the results are generally specific to one specific programme that cannot easily be applied to other situations. Meaning that knowledge is not generally transferable. Programmes are then often relegated to learning via trial and error, generally at large expense.

Also, with no understanding of the marginal costs and benefits, programmes with significant funding often greatly overspend just to be safe, essentially wasting funds that could be used elsewhere to great benefit. Likewise, programmes that are underfunded could also be wasting funds by spreading them too thin and not achieving the minimum required effort levels, thus exacerbating the problem instead of reducing it.

This paper significantly contributes to the literature by filling a much needed gap in understanding of effort and biological outcomes. We provide a method for getting much

closer to answering the above questions using a sophisticated simulation methodology rather than having to rely on costly trial and error. Our results allow for estimates of the resources needed to pursue future vaccination campaigns as well as disease elimination, reduction, or other strategies. Understanding the costs and benefits of rabies elimination and reduction strategies also improves the ability to motivate the inter-sectoral cooperative strategies needed for such strategies to be successful [87].

The limitations of this paper lie in the inability to measure or estimate the human side benefits. These benefits come in the form of reduced canine to human disease transmissions given lower disease prevalence levels in the dog population. We did not have the necessary data to perform this analysis and therefore only provided estimates on the animal side benefits. Given proper data, we could also estimate the number of human bites from canines, and the subsequent number of humans becoming infected, as well as the estimated cost of post exposure prophylaxis (PEP) likely to be administered. This is something that future applications of this model could and should address in order to gain a much more complete picture.

Beyond the insights gained from the above application, this paper outlines the individual-based stochastic simulation model of wildlife population, and how it can be used to simulate the potential impacts on a wildlife population due to disease and other management interventions. This model can be applied to various different wildlife species, disease, geographies, etc.

Managers have complete control to adapt all the model functions to fit species, geography, seasonality, etc. The functions vary across modeled locations and time periods. For example, mortality, can vary across locations and be seasonal, meaning that it could be higher for 60

days per year. Disease could be an exogenous risk to only subset of nine modeled locations. This includes management strategies being location and time specific. We present a model that provides insights into the potential impact of disease and intervention where no data may be readily available such as remote locations or in highly specific circumstances.

3.4. Bioeconomic Model

3.4.1. General Structure. BioEcon is written in R (R Core Team 2014). R was chosen over other languages because its use by researchers is common and growing, it is free, and the code is relatively easy to read. There are several key characteristics of the model. First, the model tracks individual animals and their traits through time. This is performed via a population matrix that contains a row for each living individual and a column for each trait associated with individuals (Table 3.2). Second, the model operates on a daily time step. This minimizes bias that results from discrete time steps, and enables the model to more precisely consider management efforts that vary temporally. Finally, the model contains spatial structure that consists of a grid of locations. Nine locations are available, and these may be tailored to the specific application via different carrying capacities, management strategies, immigration parameters, and any number of other parameters that govern vital rates. By default the grid is arranged with location 1 in the upper left-hand corner and location 9 in the bottom right-hand corner.

Table 3.2. Inputs used in the model and notes on input definition and usage.

Traits	**Notes**
id	a number assigned to each individual that exists in an iteration
location	indicates current location of the individual

group	indicates the group number that individual belongs to
female	1=female
day age	days since birth
juvenile	1=juvenile
mortality probability	-
mating probability	-
pregnant	1=pregnant
time pregnant	days since becoming pregnant
exposed probability	probability of contracting disease and entering exposed class
passive immunity	1=in passively immune class
natural immunity	1=in naturally immune class
susceptible	1=in susceptible class
exposed	1=in exposed class
infected	1=in infected class
recovered with immunity	1=in recovered with immunity class
time with passive immunity	days since acquiring passive immunity
time in exposed class	days since entering exposed class
time in infected class	days since entering infected class
time with immunity after recovery	days since entering recover with immunity class
time limit passive immunity	days that will be spent in passive immunity class
time limit of exposed class	days that will be spent in exposed class
time limit of infected class	days that will be spent in infected class
time limit of immunity after recovery	days that will be spent in recover with immunity class
sterile from disease	1=sterile from disease
trapped	1=trapped on current day
trapping probability	-
time trapped	time previously trapped
euthanize probability	probability if captured
sterilize probability	probability if captured
contracept probability	probability if captured
vaccinate probability	probability if captured

sterile	1=sterile
contracepted	1=contracepted
vaccinated	1=vaccinated
believed sterile	1=manager assumes sterile if captured
believed contracepted	1=manager assumes contracepted if captured
believed vaccinated	1=manager assumes vaccinated if captured
time contracepted	days since contraception
time vaccinated	days since vaccination
group-linked traits	
adult females in group	count
adult males in group	count
fertile adult females in group	count
fertile adult males in group	count
infected in group	count
location-linked traits	
abundance at location	count
K at location	carrying capacity at the individuals current location
density at location	abundance relative to carrying capacity at location
adult females at location	count
adult males at location	count
juvenile females at location	count
juvenile males at location	count
fertile adult females at location	count
fertile adult males at location	count
infected at location	count
susceptible at location	count
traps at location	count
seasonality-linked traits	
day of year	[1, 365]; same for all individuals
12 binary columns indicating month	1 for current month, 0 otherwise; same for all individuals

There are three main sections of code: inputs, functions that correspond to major biological processes, and the iteration and time loops from which the various functions are called. The first section simply assigns values to the various inputs and can be tailored to the specific application. Biological processes executed in specific functions include mortality, mating, reproduction, dispersal, immigration, disease transmission, capture, and treatment (removal, permanent sterilization, temporary contraception, vaccination). The functions that execute the biological processes constitute the bulk of code and are discussed in detail in the next sections. The time loop exists within the iteration loop and loops through the days of the specified timeframe. Each day, it calls the functions that execute the various biological processes. These functions accept the population matrix as an argument, execute the process, and return the updated population matrix. The model was structured in this way so that it is simple to change process ordering without moving large blocks of code. Additionally, the structure makes it simple to modify or add processes without disrupting or altering other parts of the model. Finally, the iteration loop performs the specified number of iterations. Due to the stochastic nature of the model, a substantial number of iterations may be required in some applications to acquire a clear understanding of the distribution of results. Iterations are executed in parallel via the doParellel and foreach packages in R. The model should be executed on a multi-core machine so that parallel processing can be exploited.

3.4.2. Mortality. The mortality function requires two inputs. The first is a function that assigns a mortality probability to each individual on the current day. This function can be as simple as a constant, or it can use any of the columns of the population matrix as arguments. For example, density dependent mortality can be accommodated by allowing

mortality probabilities to be a function of the ratio of abundance to carrying capacity at location. Sex and age-specific mortality can be accounted for by specifying a function that accepts the sex and age of the individual as arguments, and seasonal differences in mortality can be accounting for by including day of the year or the month indicators as arguments.

Mortality probabilities are updated daily. When the mortality function is called each day, a random number on [0, 1] is drawn for each individual and compared to the mortality probability. If the random draw is less than the mortality probability, the individual is removed from the population matrix. In addition to this mortality process, the population can be optionally censored to carrying capacity each day. This process occurs by randomly removing individuals from the population until carrying capacity is reached. Once these processes have been completed, the updated population matrix is returned to the time loop.

3.4.3. Mating and Reproduction. Mating and reproduction processes are executed by two separate functions. The mating function relies on mating probabilities returned from a specified function. Like the mortality probability function, the mating probability function can be as simple as a constant, or it can include many arguments. Note that mating probabilities of adult females are automatically considered zero if the individual is not fertile or there are no fertile males within the location. Random numbers on [0, 1] are drawn and compared to each fertile female's probability of mating. If the draw is less than the probability, the female becomes pregnant.

New litters are created by the reproduction function. When a female has been pregnant for the specified gestation period, a litter size is selected based on a specified vector of probabilities. Each individual within the litter is randomly assigned a sex based on the specified fraction of offspring that are female. New individuals are added to the population

matrix and the relevant columns filled (e.g. id, location, sex). The updated population matrix is then returned to the time loop.

3.4.4. Dispersal. Dispersal refers to an individual's dispersal from their current group or juveniles dispersal from their mother. Juveniles automatically disperse at a specified age, while other dispersal may occur based on defined rules governing group demographics. A number of different rules are available. The model allows no group structure, female-only groups, or groups that contain both sexes. When specified limits on group demographics are reached, individuals are randomly selected for dispersal. When an individual is selected for dispersal, the individual disperses to a new group based on a specified objective. Three options are available: (1) minimize intra-group competition from the same sex, (2) maximize intra-group abundance of the opposite sex, and (3) minimize the number of adults in the group.

Dispersal operates sequentially but randomly. That is, each day all individuals are evaluated in random order to determine if dispersal is required. If an individual must disperse because it has reached the age of dispersal or its group demographics are not within limits, the individual disperses to a new group based on the specified objective, and all group statistics are updated before the next individual is evaluated. This sequential process ensures reasonable dispersal dynamics, but it also slows execution considerably. Once all individuals have been evaluated, the updated population matrix is returned to the time loop.

3.4.5. Immigration. Unlike dispersal, immigration occurs simultaneously each day based on probabilities returned from a specified function. Similar to mortality and mating probabilities, it is straightforward to let the immigration probabilities be a function of any number of individual, group, or location characteristics (e.g. abundance relative to carrying capacity

at location). If a group structure is specified, immigration takes place at the group level (i.e. groups immigrate to new locations as a whole). Individuals or groups can move to new locations with several different specified objectives. Groups (or individuals in the case of no group structure) can move randomly to a new location or they may move by choosing a location with minimum abundance relative to carrying capacity. For solo males, there is an additional option of choosing a new location based on minimum abundance of solo males. Finally, the user may specify which movements are feasible within the grid structure. For example, it may be reasonable to limit daily movements to bordering cells.

Immigration is executed similar to other processes. A random number on [0, 1] is drawn for each group or individual and compared to the immigration probability. A new location is selected randomly from the subset of feasible location, or the new location is set based on the specified objective. Once new locations are determined, the population matrix is updated and returned to the time loop.

3.4.6. Disease. BioEcon allows the following disease states: susceptible, exposed, infected, recovered with immunity, born with passive immunity, and natural immunity. By default, individuals in the exposed state are not yet capable of transmitting the disease, but they will enter the infected class with certainty assuming they live long enough. The number of days spent in each disease state is specified, and states that are not relevant for a particular disease can be ignored by entering zero for time spent in the state. Three outcomes are possible after infection: return to susceptibility, recover with immunity, and death. These outcomes are governed by three specified probabilities. Thus, if the application examines a disease with a mortality rate of one, the probability of death after infection would be set at one.

BioEcon can be used to model population dynamics in the absence of disease. To remove disease processes from the model, the day the disease is introduced is simply set beyond the time frame of the simulation. This ensures that all individuals will always be in the susceptible state. When specified this way, all other disease-related inputs are ignored by the model. If disease dynamics are to be modeled, the day the disease will be introduced and the number of individuals that will initially be exposed must be specified. Alternatively, it is possible to specify an exogenous probability of exposure and the day of the iteration that this probability becomes non-zero.

Disease transmission is governed by probabilities returned by a specified function. Thus, the model can easily be tailored to density-dependent transmission, frequency-dependent transmission, or more exotic forms of transmission. Each day, random numbers on [0, 1] are compared to transmission probabilities. Individuals that are exposed are moved into the exposed state and a timer is started. Additionally, each day all individuals in the exposed, infected, recovered with immunity, and passively immune states are evaluated. If an individual has been in a particular state for the specified maximum time, the individual transitions to the next state. For individuals moving out of the infected state, an additional random number draw determines their fate.

3.4.7. Capture. The number of units of effort (e.g. traps, labor hours) used each day at each location must be specified. An effort unit cost is also specified so that the total cost of capture effort on each day at each location can be calculated. Another specified function returns capture probabilities for each individual on each day. Typically, this function will take the units of effort at location as an argument so that the probability of being captured is zero if no effort is expended and the probability increases as effort increases. Other possible

arguments include abundance at location, age, sex, and the number of times the animal has been trapped or captured previously. If a random number draw on [0, 1] is less than the individuals probability of being trapped, the individual is marked as captured.

3.4.8. Policy or Treatment. Once an individual is marked as captured, a number of different policies or treatments are possible. The elements of an array define the fraction of captured animals that receive each treatment. The policy array has a row for each day of the iteration, a column for each location, and a sheet for each policy (i.e. removal, sterilization, contraception, and vaccination). A separate policy array must be specified for each of four classes of individual: juvenile female, juvenile male, adult female, and adult male. All elements of the first three sheets of these arrays must be on the [0, 1] interval and are interpreted by the model as the fraction of animals of that class captured on a particular day that receive a particular treatment. A given row and column of the array must sum to one across the first three sheets; otherwise the implication is that some animals receive both contraception and sterilization or receive fertility treatment at the time they are removed from the population. The fourth sheet of all arrays represents vaccination and is restricted to zero or one. If the element equals one, then all animals of that particular class and at that location that are captured on that day will be vaccinated if they are released (not removed). A zero implies they will be released without vaccination.

3.4.9. Management Costs. Two types of management costs are specified: the cost of a unit of effort (e.g. the per day cost associated with a single capture team) and the cost of each policy of treatment on a per animal basis. Sterilization and contraception costs are sex-specific, but removal and vaccination costs apply to both sexes. The model calculates

total trapping costs each day based on the units of effort, and it calculates daily treatment costs separately for the four classes of individuals based on the number of individuals captured and the treatments they receive.

3.4.10. Benefits. Calculating the benefits of a management strategy requires two steps. We assume that benefits arise from a strategy through a reduction in some negative impact or an increase in some positive impact. Thus, the impact must be measured under some baseline scenario (e.g. no management or current strategy) and under the proposed strategy. To enable this, up to five impact functions can be specified. These functions can accept any of the columns of the population matrix as arguments, and their output may represent an impact measured in monetary terms (e.g. crop damage) or a non-monetary impact (e.g. potential human exposures to a disease).

Bibliography

[1] G. B. of Disease, "Global burden of disease study 2010," tech. rep., Institute for Health Metrics and Evaluation (IHME), 2013.

[2] H. Wang, L. Dwyer-Lindgren, K. T. Lofgren, J. K. Rajaratnam, J. R. Marcus, A. Levin-Rector, C. E. Levitz, A. D. Lopez, and C. J. Murray, "Age-specific and sex-specific mortality in 187 countries, 1970–2010: a systematic analysis for the global burden of disease study 2010," *The Lancet*, vol. 380, no. 9859, pp. 2071–2094, 2013.

[3] G. S. Becker, T. J. Philipson, and R. R. Soares, "The quantity and quality of life and the evolution of world inequality," *American Economic Review*, vol. 95, no. 1, pp. 277–291, 2005.

[4] H. Bleakley, "Disease and development: evidence from hookworm eradication in the american south," *The Quarterly Journal of Economics*, vol. 122, no. 1, p. 73, 2007.

[5] E. Lam, "Controlled cell death, plant survival and development," *Nature Reviews Molecular Cell Biology*, vol. 5, no. 4, pp. 305–315, 2004.

[6] D. E. Bloom, D. Canning, and J. Sevilla, "Health and economic growth: reconciling the micro and macro evidence," *Center on Democracy, Development and the Rule of Law Working Papers*, 2005.

[7] D. Acemoglu and S. Johnson, "Disease and development: the effect of life expectancy on economic growth," tech. rep., National Bureau of Economic Research, 2006.

[8] J. L. Gallup and J. D. Sachs, "The economic burden of malaria," *The American journal of tropical medicine and hygiene*, vol. 64, no. 1 suppl, pp. 85–96, 2001.

[9] C. J. Ruhm, "Current and future prevalence of obesity and severe obesity in the united states," in *Forum for Health Economics & Policy*, vol. 10, 2007.

[10] A. M. Wolf and G. A. Colditz, "Current estimates of the economic cost of obesity in the united states," *Obesity research*, vol. 6, no. 2, pp. 97–106, 1998.

[11] D. Thompson, J. Edelsberg, K. L. Kinsey, and G. Oster, "Estimated economic costs of obesity to us business," *American Journal of Health Promotion*, vol. 13, no. 2, pp. 120–127, 1998.

[12] C. L. Baum and W. F. Ford, "The wage effects of obesity: a longitudinal study," *Health Economics*, vol. 13, no. 9, pp. 885–899, 2004.

[13] S. Morris, "The impact of obesity on employment," *Labour Economics*, vol. 14, no. 3, pp. 413–433, 2007.

[14] J. D. Sachs and A. M. Warner, "Fundamental sources of long-run growth," *The American Economic Review*, pp. 184–188, 1997.

[15] S. Du, T. A. Mroz, F. Zhai, and B. M. Popkin, "Rapid income growth adversely affects diet quality in chinaparticularly for the poor!," *Social science & medicine*, vol. 59, no. 7, pp. 1505–1515, 2004.

[16] P. Anand, C. Sundaram, S. Jhurani, A. B. Kunnumakkara, and B. B. Aggarwal, "Curcumin and cancer: an old-age disease with an age-old solution," *Cancer letters*, vol. 267, no. 1, pp. 133–164, 2008.

[17] S. C. Datta and J. J. Reimer, "Malaria and economic development," *Review of Development Economics*, vol. 17, no. 1, pp. 1–15, 2013.

[18] J. Angrist and G. Imbens, "Identification and estimation of local average treatment effects," 1995.

[19] J. Heckman, "Instrumental variables: A study of implicit behavioral assumptions used in making program evaluations," *Journal of human resources*, pp. 441–462, 1997.

[20] D. Jones, "The economics of exclusion restrictions in iv models," tech. rep., National Bureau of Economic Research, 2015.

[21] J. D. Angrist and A. B. Krueger, "Empirical strategies in labor economics," *Handbook of labor economics*, vol. 3, pp. 1277–1366, 1999.

[22] B. D. Meyer, "Natural and quasi-experiments in economics," *Journal of business & economic statistics*, vol. 13, no. 2, pp. 151–161, 1995.

[23] E. Fichera and D. Savage, "Income and health in tanzania. an instrumental variable approach," *World development*, vol. 66, pp. 500–515, 2015.

[24] M. Lindahl, "Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income," *Journal of Human resources*, vol. 40, no. 1, pp. 144–168, 2005.

[25] M. Schnalzenberger, "Causal effect of income on health: Investigating two closely related policy reforms in austria," *The Journal of the Economics of Ageing*, vol. 7, pp. 6–16, 2016.

[26] A. Ahammer, G. Thomas Horvath, and R. Winter-Ebmer, "The effect of income on mortalitynew evidence for the absence of a causal link," *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 2016.

[27] J. D. Sachs, "Institutions don't rule: direct effects of geography on per capita income," tech. rep., National Bureau of Economic Research, 2003.

[28] D. E. Sahn and H. Alderman, "The effects of human capital on wages, and the determinants of labor supply in a developing country," *Journal of Development Economics*, vol. 29, no. 2, pp. 157–183, 1988.

[29] T. P. Schultz and A. Tansel, "Wage and labor supply effects of illness in cote d'ivoire and ghana: Instrumental variable estimates for days disabled," *Journal of development economics*, vol. 53, no. 2, pp. 251–286, 1997.

[30] S. M. Haffner, S. Lehto, T. Rönnemaa, K. Pyörälä, and M. Laakso, "Mortality from coronary heart disease in subjects with type 2 diabetes and in nondiabetic subjects with and without prior myocardial infarction," *New England journal of medicine*, vol. 339, no. 4, pp. 229–234, 1998.

[31] G. E. Battese, "A note on the estimation of cobb-douglas production functions when some explanatory variables have zero values," *Journal of agricultural Economics*, vol. 48, no. 1-3, pp. 250–252, 1997.

[32] D. Filmer, "Fever and its treatment among the more and less poor in sub-saharan africa," *Health policy and planning*, vol. 20, no. 6, pp. 337–346, 2005.

[33] G. Wobeser, "Disease management strategies for wildlife," *Revue Scientifique et Technique-Office international des epizooties*, vol. 21, no. 1, pp. 159–178, 2002.

[34] F. A. Leighton, "Foreign animal diseases and canadian wildlife: reasons for concern and the elements of preparedness," *The Canadian Veterinary Journal*, vol. 43, no. 4, p. 265, 2002.

[35] USDA-APHIS, "Foot-and-mouth disease response plan," tech. rep., , 2014.

[36] G. J. Hickling, "Dynamics of bovine tuberculosis in wild white-tailed deer in michigan," 2002.

[37] R. D. Horan and C. A. Wolf, "The economics of managing infectious wildlife disease," *American Journal of Agricultural Economics*, vol. 87, no. 3, pp. 537–551, 2005.

[38] H. McCallum, N. Barlow, and J. Hone, "How should pathogen transmission be modelled?," 2001.

[39] G. Smith and C. Cheeseman, "A mathematical model for the control of diseases in wildlife populations: culling, vaccination and fertility control," *Ecological Modelling*, vol. 150, no. 1, pp. 45–53, 2002.

[40] P. Daszak, A. A. Cunningham, and A. D. Hyatt, "Emerging infectious diseases of wildlife–threats to biodiversity and human health," *science*, vol. 287, no. 5452, pp. 443–449, 2000.

[41] D. Grenier, C. Barrette, and M. Crête, "Food access by white-tailed deer (odocoileus virginianus) at winter feeding sites in eastern quebec," *Applied Animal Behaviour Science*, vol. 63, no. 4, pp. 323–337, 1999.

[42] M. S. Garner, "Movement patterns and behavior at winter-feeding and fall baiting stations in a population of white-tailed deer infected with bovine tuberculosis in the northeastern lower peninsula of michigan," 2001.

[43] E. P. Fenichel and R. D. Horan, "Jointly-determined ecological thresholds and economic trade-offs in wildlife disease management," *Natural Resource Modeling*, vol. 20, no. 4, pp. 511–547, 2007.

[44] E. B. Barbier, "A note on the economics of biological invasions," *Ecological Economics*, vol. 39, no. 2, pp. 197–202, 2001.

[45] G. Feder and U. Regev, "Biological interactions and environmental effects in the economics of pest control," *Journal of Environmental Economics and Management*, vol. 2, no. 2, pp. 75–91, 1975.

[46] L. J. Olson *et al.*, "The economics of terrestrial invasive species: a review of the literature," *Agricultural and Resource Economics Review*, vol. 35, no. 1, p. 178, 2006.

[47] W. Brock and A. Xepapadeas, "Optimal ecosystem management when species compete for limiting resources," *Journal of Environmental Economics and Management*, vol. 44, no. 2, pp. 189–220, 2002.

[48] W. J. Ströbele and H. Wacker, "The economics of harvesting predator-prey systems," *Journal of Economics*, vol. 61, no. 1, pp. 65–81, 1995.

[49] K. Chaudhuri, "A bioeconomic model of harvesting a multispecies fishery," *Ecological Modelling*, vol. 32, no. 4, pp. 267–279, 1986.

[50] D. Moon, J. Moon, and A. Keagy, "Direct and indirect interactions," *Nat Educ Knowl*, vol. 1, no. 9, 2010.

[51] R. T. Melstrom and R. D. Horan, "Interspecies management and land use strategies to protect endangered species," *Environmental and Resource Economics*, vol. 58, no. 2, pp. 199–218, 2014.

[52] A. Dobson and A. Lyles, "Black-footed ferret recovery," *Science(Washington)*, vol. 288, no. 5468, pp. 985–988, 2000.

[53] BFFRP, "Black-footed ferret recovery program: Reintroduction," 2015.

[54] J. N. Pauli, S. W. Buskirk, E. S. Williams, and W. H. Edwards, "A plague epizootic in the black-tailed prairie dog (Cynomys ludovicianus).," *Journal of wildlife diseases*, vol. 42, no. 1, pp. 74–80, 2006.

[55] S. K. Collinge, W. C. Johnson, C. Ray, R. Matchett, J. Grensten, J. F. Cully Jr, K. L. Gage, M. Y. Kosoy, J. E. Loye, and A. P. Martin, "Landscape structure and plague

occurrence in black-tailed prairie dogs on grasslands of the western usa," *Landscape ecology*, vol. 20, no. 8, pp. 941–955, 2005.

[56] T. E. Rocke, S. R. Smith, D. T. Stinchcomb, and J. E. Osorio, "Immunization of black-tailed prairie dog against plague through consumption of vaccine-laden baits," *Journal of Wildlife Diseases*, vol. 44, no. 4, pp. 930–937, 2008.

[57] J. S. Mencher, S. R. Smith, T. D. Powell, D. T. Stinchcomb, J. E. Osorio, and T. E. Rocke, "Protection of black-tailed prairie dogs (cynomys ludovicianus) against plague after voluntary consumption of baits containing recombinant raccoon poxvirus vaccine," *Infection and immunity*, vol. 72, no. 9, pp. 5502–5505, 2004.

[58] D. W. Tripp, T. E. Rocke, S. P. Streich, N. L. Brown, J. R.-R. Fernandez, and M. W. Miller, "Season and application rates affect vaccine bait consumption by prairie dogs in colorado and utah, usa," *Journal of wildlife diseases*, vol. 50, no. 2, pp. 224–234, 2014.

[59] J. F. Cully and E. S. Williams, "Interspecific comparisons of sylvatic plague in prairie dogs," 2001.

[60] M. G. Bhat and R. G. Huffaker, "Management of a transboundary wildlife population: A self-enforcing cooperative agreement with renegotiation and variable transfer payments," *Journal of Environmental Economics and Management*, vol. 53, no. 1, pp. 54–67, 2007.

[61] M. G. Bhat, R. G. Huffaker, and S. M. Lenhart, "Controlling transboundary wildlife damage: modeling under alternative management scenarios," *Ecological modelling*, vol. 92, no. 2, pp. 215–224, 1996.

[62] S. A. Robertson, "A review of feral cat control," *Journal of Feline Medicine and Surgery*, vol. 10, no. 4, pp. 366–375, 2008.

[63] L. Wahlström and O. Liberg, "Patterns of dispersal and seasonal migration in roe deer (capreolus capreolus)," *Journal of Zoology*, vol. 235, no. 3, pp. 455–467, 1995.

[64] D. E. Biggins, B. J. Miller, L. R. Hanebury, B. Oakleaf, A. H. Farmer, R. Crete, and A. Dood, "A technique for evaluating Black-Footed Ferret habitat," in *Proceedings of the symposium on the management of prairie dog complexes for the reintroduction of the black-footed ferret*, (Washington, D.C.), pp. 73–88, Fish and Wildlife Service, 1993.

[65] R. L. Griebel, "Conata basin/badlands area 2014 plague management report," tech. rep., US Forest Service, 2014.

[66] R. Hansen, D. Uresk, and R. Cincotta, "Prairie dog dispersal and habitat preference in badlands national park," *University of Wyoming National Park Service Research Center Annual Report*, vol. 6, no. 1, pp. 6–10, 1982.

[67] C. M. Nistler, "A review of prairie dog population demographics and implications for management in Montana," tech. rep., Montana Fish, Wildlife and Parks, Helena Montana, 2009.

[68] "Black-footed Ferret Population Management Planning Workshop," tech. rep., IUCN/SSC Conservation Breeding Sp ecialist Group: Apple Valley, MN, 2004.

[69] C. T. Webb, C. P. Brooks, K. L. Gage, and M. F. Antolin, "Classic flea-borne transmission does not drive plague epizootics in prairie dogs," *Proceedings of the National Academy of Sciences*, vol. 103, no. 16, pp. 6236–6241, 2006.

[70] S. C. Forrest, D. E. Biggins, L. Richardson, T. W. Clark, T. M. Campbell, K. A. Fagerstone, and E. T. Thorne, "Population attributes for the black-footed ferret (mustela nigripes) at meeteetse, wyoming, 1981–1985," *Journal of Mammalogy*, vol. 69, no. 2, pp. 261–273, 1988.

[71] J. Cully Jr, "Growth and life-history changes in Gunnison's prairie dogs after a plague epizootic," *Journal of Mammalogy*, vol. 78, no. 1, pp. 146–157, 1997.

[72] J. H. Shaw, "Assessment of black-tailed prairie dog colonies for reintroduction of black-footed ferrets in western oklahoma," in *Proceedings of the Oklahoma Academy of Science*, vol. 73, pp. 47–52, 1993.

[73] S. A. Shwiff, K. N. Kirkpatrick, and R. T. Sterner, "Economic evaluation of an oral rabies vaccination program for control of a domestic dog–coyote rabies epizootic: 1995–2006," *Journal of the American Veterinary Medical Association*, vol. 233, no. 11, pp. 1736–1741, 2008.

[74] L. Nel and C. Rupprecht, "Emergence of lyssaviruses in the old world: the case of africa," in *Wildlife and Emerging Zoonotic Diseases: The Biology, Circumstances and Consequences of Cross-Species Transmission*, pp. 161–193, Springer, 2007.

[75] S. W. Seagle and J. D. Close, "Modeling white-tailed deer odocoileus virginianus population control by contraception," *Biological Conservation*, vol. 76, no. 1, pp. 87–91, 1996.

[76] J. Xie, H. R. Hill, S. R. Winterstein, H. Campa, R. V. Doepker, T. R. Van Deelen, and J. Liu, "White-tailed deer management options model (deermom): design, quantification, and application," *Ecological Modelling*, vol. 124, no. 2, pp. 121–130, 1999.

[77] M. K. Cosgrove, H. Campa, D. S. Ramsey, S. M. Schmitt, and D. J. O'brien, "Modeling vaccination and targeted removal of white-tailed deer in michigan for bovine tuberculosis control," *Wildlife Society Bulletin*, vol. 36, no. 4, pp. 676–684, 2012.

[78] D. Rondeau, "Along the way back from the brink," *Journal of Environmental Economics and Management*, vol. 42, no. 2, pp. 156–182, 2001.

[79] D. Rondeau and J. M. Conrad, "Managing urban deer," *American Journal of Agricultural Economics*, vol. 85, no. 1, pp. 266–281, 2003.

[80] E. P. Fenichel and R. D. Horan, "Gender-based harvesting in wildlife disease management," *American Journal of Agricultural Economics*, vol. 89, no. 4, pp. 904–920, 2007.

[81] K. Hampson, J. Dushoff, J. Bingham, G. Brückner, Y. Ali, and A. Dobson, "Synchronous cycles of domestic dog rabies in sub-saharan africa and the impact of control efforts," *Proceedings of the National Academy of Sciences*, vol. 104, no. 18, pp. 7717–7722, 2007.

[82] P. Kitala, J. McDermott, P. Coleman, and C. Dye, "Comparison of vaccination strategies for the control of dog rabies in machakos district, kenya," *Epidemiology and Infection*, vol. 129, no. 01, pp. 215–222, 2002.

[83] K. Hampson, J. Dushoff, S. Cleaveland, D. T. Haydon, M. Kaare, C. Packer, and A. Dobson, "Transmission dynamics and prospects for the elimination of canine rabies," *PLoS Biol*, vol. 7, no. 3, p. e1000053, 2009.

[84] P. Kitala, J. McDermott, M. Kyule, J. Gathuma, B. Perry, and A. Wandeler, "Dog ecology and demography information to support the planning of rabies control in machakos district, kenya," *Acta tropica*, vol. 78, no. 3, pp. 217–230, 2001.

[85] S. Pal, "Parental care in free-ranging dogs, canis familiaris," *Applied Animal Behaviour Science*, vol. 90, no. 1, pp. 31–47, 2005.

[86] P. W. Concannon, "Reproductive cycles of the domestic bitch," *Animal reproduction science*, vol. 124, no. 3, pp. 200–210, 2011.

[87] F.-X. Meslin and D. Briggs, "Eliminating canine rabies, the principal source of human infection: what will it take?," *Antiviral research*, vol. 98, no. 2, pp. 291–296, 2013.

APPENDIX A

Additional Tables

Table A.1. Full list of causes of mortality and disability

2 Wheel road injury	Maternal sepsis
4 Wheel road injury	Measles
Abortion	Mechanical forces
Acne vulgaris	Mechanical forces: firearm
Acute hepatitis A	Melanoma
Acute hepatitis B	Meningitis
Acute hepatitis C	Meningococcal
ADHD	Mental and behavioral disorders
Adverse medical treatment	Migraine
Alcohol use disorders	Mouth cancer
Alopecia areata	Multiple sclerosis
Alzheimer's disease	Musculoskeletal disorders
Amphetamine use	Myeloma
Animal contact	Nasopharynx cancer
Anxiety disorders	Neck pain
Aortic aneurysm	Neonatal disorders
Appendicitis	Neonatal encephalopathy
Asperger's	Neonatal sepsis
Assault by firearm	Neural tube defects
Assault by other means	Neurological disorders
Assault by sharp object	Non Hodgkin lymphoma
Asthma	Non melanoma skin cancer
Atrial fibrillation	Nutritional deficiencies
Autism	Obstructed labor
Bacterial skin diseases	Opioid use
Benign prostatic hyperplasia	Oral disorders
Bicycle road injury	Osteoarthritis
Bipolar disorder	Other: cancers
Bladder cancer	Other: cardio circulatory
Brain cancer	Other: chromosomal anomalies
Breast cancer	Other: CKD
Cannabis use	Other: communicable

Cardio and circulatory diseases
Cardiomyopathy
Cataract
Cellulitis
Cervical cancer
Childhood behavorial disorders
Chlamydia
Chronic kidney disease
Chronic respiratory diseases
Cirrhosis
Cleft lip
Cocaine use
Colorectal cancer
Conduct disorder
Congenital anomalies
Congenital heart anomalies
COPD
Decubitus ulcer
Dengue
Dental caries
Diabetes
Diabetic CKD
Diarrheal diseases
Digestive diseases
Diptheria
Downs syndrome
Drowning
Dysthymia
Eating disorders
Eczema
Edentulism
Encephalitis
Endocarditis
Endometriosis
Epilepsy
Esophageal cancer
Falls
Female infertility
Other: congenital anomalies
Other: digestive diseases
Other: drug use
Other: endocrine
Other: gynecological disorders
Other: hearing loss
Other: hemog
Other: infectious diseases
Other: maternal disorders
Other: mechanical forces
Other: meningitis
Other: mental and behavioral
Other: musculoskeletal
Other: neonatal disorders
Other: neurological disorders
Other: non communicable
Other: NTD
Other: nutritional deficiencies
Other: pharynx cancer
Other: respiratory diseases
Other: road injury
Other: sense organ disorders
Other: skin diseases
Other: STDs
Other: transport injuries
Other: unintentional injuries
Other: urinary diseases
Other: vision loss
Otitis media
Ovarian cancer
Pancreatic cancer
Pancreatitis
Parkinson s disease
Pedestrian road injury
Peptic ulcer
Periodontal disease
Peripheral vascular disease
Pervasive developmental disorders

Fibroids
Fire
Fungal skin diseases
G6PD deficiency
Gall bladder diseases
Gallbladder cancer
Gastrititis and duodenitis
Genital prolapse
Glaucoma
Glomerulonephritis
Gonnorhea
Gout
Gynecological diseases
Hemoglobinopathies
Hemorrhagic stroke
HiB meningitis
HIV AIDS
Hodgkin s lymphoma
Hypertensive CKD
Hypertensive heart disease
Inflammatory bowel disease
Inguinal and femoral hernia
Intellectual disability
Interpersonal violence
Interstitial lung diseases
Intestinal obstructions
Iodine deficiency
Iron deficiency anemia
Ischemic heart disease
Ischemic stroke
Kidney cancers
Larynx cancer
Leprosy
Leukemia
Liver cancer
Low back pain
Lower respiratory infections
Lung cancer
Pneumococcal meningitis
Pneumoconiosis
Poisonings
Polycystic ovary
Premenstrual syndrome
Preterm birth complications
Prostate cancer
Pruritus
Psoriasis
Pyelonephritis and UTI
Rabies
Refraction disorders
Rheumatic heart disease
Rheumatoid arthritis
Road injury
Scabies
Schizophrenia
Self harm
Sense organ diseases
Sickle cell
SIDS
Stomach cancer
Stroke
Syphilis
Tension type headache
Testicular cancer
Tetanus
Thalassemia
Thyroid cancer
Transport injuries
Trichomoniasis
Tuberculosis
Typhoid fevers
Unintentional injuries
Unipolar depressive disorders
Upper respiratory infections
Urinary diseases
Urolithiasis

Macular degeneration	Urticaria
Major depressive disorder	Uterine cancer
Malaria	Varicella
Male infertility	Vascular intestinal disorders
Malnutrition	Viral skin diseases
Maternal hemorrhage	Whooping cough
Maternal hypertension	

TABLE A.2. Income Ranked Cause List With Expected Per Capita Income and Max Density. 1990

Cause	Expected Income	Standard Deviation	Max Density	Expected Age Group
Tetanus	624	4.13	0.357	0-14
Malaria	651	13.05	0.106	0-14
Measles	725	8.15	0.179	0-14
Obstructed labor	789	7.03	0.267	15-64
Diptheria	794	9.03	0.429	0-14
Diarrheal diseases	983	6.42	0.413	0-14
Syphilis	1,018	9.71	0.322	0-14
Maternal sepsis	1,038	8.15	0.343	15-64
Rabies	1,068	15.91	0.320	15-64
Protein-energy malnutrition	1,069	9.77	0.410	65+
Whooping cough	1,093	7.55	0.367	0-14
Glomerulonephritis	1,119	7.08	0.501	65+
Abortion	1,152	8.19	0.412	15-64
Maternal hemorrhage	1,161	11.37	0.330	15-64
HiB meningitis	1,171	6.68	0.586	0-14
Pneumococcal meningitis	1,173	5.97	0.500	0-14
Other: maternal disorders	1,250	10.04	0.458	15-64
Acute hepatitis A	1,250	10.51	0.348	65+
Maternal hypertension	1,301	11.25	0.405	15-64
Neonatal sepsis	1,358	10.34	0.374	0-14
Animal contact	1,384	9.02	0.408	0-14
Nutritional deficiencies	1,395	9.87	0.359	65+
Meningococcal	1,437	9.05	0.319	0-14
Meningitis	1,528	8.74	0.470	0-14
Otitis media	1,542	5.62	0.728	0-14

Tuberculosis	1,597	9.12	0.425	65+
Other: neonatal disorders	1,722	13.42	0.439	0-14
Upper respiratory infections	1,806	19.48	0.337	65+
Typhoid fevers	1,833	23.61	0.292	15-64
Encephalitis	1,937	15.55	0.377	0-14
Other: infectious diseases	1,995	22.09	0.382	0-14
Other: meningitis	2,046	13.94	0.388	0-14
Neonatal disorders	2,098	15.86	0.484	0-14
Neonatal encephalopathy	2,124	19.09	0.414	0-14
Mechanical forces (firearm)	2,227	19.26	0.347	15-64
Sickle cell	2,339	33.51	0.208	0-14
HIV AIDS	2,390	41.44	0.153	15-64
Cleft lip and palate	2,557	21.89	0.334	0-14
Acute hepatitis B	2,625	22.64	0.271	65+
Preterm birth complications	2,672	21.84	0.361	0-14
Varicella	2,725	18.12	0.445	0-14
Appendicitis	2,821	19.74	0.255	65+
Epilepsy	2,875	20.23	0.340	65+
Iron-deficiency anemia	3,000	26.74	0.188	65+
Neural tube defects	3,072	30.34	0.300	0-14
Fire	3,077	22.03	0.333	65+
Mechanical forces	3,258	21.20	0.263	15-64
Other: NTD	3,461	38.25	0.289	0-14
Other: road injury	3,471	56.69	0.378	65+
Poisonings	3,499	31.79	0.300	0-14
Lower respiratory infections	3,644	33.00	0.402	0-14
Bacterial skin diseases	3,691	36.16	0.306	65+
Other: congenital anomalies	3,698	28.19	0.287	0-14
Hemoglobinopathies	3,764	33.31	0.358	0-14
Assault by sharp object	3,919	37.63	0.258	15-64
Drowning	3,949	28.48	0.256	0-14
Assault by other means	3,979	29.83	0.231	0-14
Cellulitis	4,009	39.17	0.313	65+
Other: skin diseases	4,110	40.21	0.318	65+
Congenital anomalies	4,139	29.28	0.254	0-14
Interpersonal violence	4,140	40.08	0.231	0-14
Other: STDs	4,220	44.21	0.257	65+
Chlamydia	4,248	44.63	0.256	65+

Gonnorhea	4,248	44.68	0.257	65+
Down's syndrome	4,319	33.84	0.233	0-14
Other: nutritional deficiencies	4,325	53.50	0.123	65+
Other: mechanical forces	4,408	35.49	0.240	15-64
Assault by firearm	4,480	66.21	0.220	15-64
Iodine deficiency	4,627	43.64	0.163	65+
Pedestrian road injury	4,693	45.29	0.268	65+
Other: chromosomal anomalies	4,715	37.91	0.268	0-14
Asthma	4,750	42.12	0.296	65+
Thalassemia	4,804	58.11	0.227	0-14
Other: hemog	4,817	45.81	0.300	0-14
Other: unintentional injuries	4,926	47.74	0.284	0-14
Congenital heart anomalies	4,954	36.61	0.229	0-14
Acute hepatitis C	4,979	58.18	0.195	65+
Unintentional injuries	5,034	43.84	0.283	0-14
Adverse medical treatment	5,222	74.50	0.274	0-14
Cervical cancer	5,389	42.71	0.208	65+
Other: transport injuries	5,522	56.76	0.250	15-64
Other: gynecological disorders	5,606	63.64	0.210	65+
Other: respiratory diseases	5,649	66.19	0.292	0-14
Gynecological diseases	5,873	66.36	0.202	65+
Fibroids	5,988	89.09	0.210	15-64
Inguinal and femoral hernia	6,015	47.07	0.164	65+
G6PD deficiency	6,106	53.10	0.273	65+
Other: urinary diseases	6,380	69.42	0.250	65+
Peptic ulcer	6,396	62.73	0.262	65+
Dengue	6,589	67.61	0.214	65+
Schizophrenia	6,674	80.61	0.201	65+
Transport injuries	6,748	60.12	0.242	15-64
Road injury	6,843	61.51	0.242	15-64
SIDS	6,943	77.63	0.275	0-14
Other: digestive diseases	7,015	74.36	0.276	65+
Intestinal obstructions	7,020	79.31	0.230	65+
Pneumoconiosis	7,088	97.52	0.290	65+
Inflammatory bowel disease	7,099	76.29	0.319	65+
Bicycle road injury	7,192	73.24	0.240	65+
Gastrititis and duodenitis	7,195	62.14	0.191	65+
Cirrhosis	7,216	72.77	0.229	65+

Liver cancer	7,269	80.30	0.247	65+
Decubitus ulcer	7,292	94.36	0.265	65+
Digestive diseases	7,328	71.71	0.253	65+
Rheumatic heart disease	7,520	75.07	0.241	65+
Endometriosis	7,635	263.65	0.212	15-64
Urolithiasis	7,663	77.73	0.228	65+
Cardiomyopathy	7,767	70.14	0.216	65+
Chronic respiratory diseases	7,771	77.36	0.254	65+
Diabetes	7,792	69.42	0.190	65+
Hemorrhagic stroke	7,797	79.08	0.204	65+
Hypertensive CKD	8,117	69.53	0.199	65+
Endocarditis	8,197	88.02	0.208	0-14
Other: neurological disorders	8,281	85.08	0.216	65+
2 Wheel road injury	8,352	88.84	0.257	15-64
Hypertensive heart disease	8,371	79.60	0.178	65+
4 Wheel road injury	8,388	85.37	0.218	15-64
Eating disorders	8,443	125.30	0.181	65+
Chronic kidney disease	8,443	77.34	0.214	65+
Pancreatitis	8,526	78.62	0.213	65+
Other: CKD	8,529	81.79	0.233	65+
Nasopharynx cancer	8,532	114.54	0.183	65+
Diabetic CKD	8,584	86.06	0.195	65+
Other: mental and behavioral	8,740	137.59	0.199	65+
Hodgkin's lymphoma	8,751	79.59	0.162	65+
Cocaine use	8,859	159.40	0.174	0-14
Other: endocrine	8,991	99.86	0.208	0-14
Esophageal cancer	9,028	96.84	0.202	65+
COPD	9,186	98.40	0.224	65+
Other: drug use	9,210	151.71	0.163	0-14
Stroke	9,358	87.83	0.191	65+
Gall bladder diseases	9,637	100.48	0.210	65+
Urinary diseases	9,796	108.62	0.250	65+
Other: musculoskeletal	9,868	113.51	0.191	65+
Other: cancers	9,874	106.27	0.220	65+
Amphetamine use	9,885	159.39	0.154	0-14
Stomach cancer	10,157	105.71	0.172	65+
Musculoskeletal disorders	10,245	118.03	0.245	65+
Larynx cancer	10,312	100.92	0.147	65+

Mental and behavioral disorders	10,353	114.32	0.167	65+
Non-melanoma skin cancer	10,361	98.42	0.176	65+
Rheumatoid arthritis	10,684	146.83	0.276	65+
Other: pharynx cancer	10,837	123.47	0.186	65+
Testicular cancer	10,838	139.63	0.170	65+
Ischemic stroke	10,860	103.96	0.168	65+
Self harm	10,889	119.70	0.180	15-64
Cardio and circulatory diseases	10,889	108.16	0.171	65+
Falls	11,008	144.96	0.268	65+
Mouth cancer	11,142	115.54	0.173	65+
Neurological disorders	11,187	145.08	0.282	65+
Alcohol use disorders	11,213	136.15	0.121	15-64
Interstitial lung diseases	11,636	143.12	0.189	65+
Pyelonephritis and UTI	11,733	133.97	0.176	65+
Other: cardio and circulatory	11,904	135.40	0.174	65+
Leukemia	12,007	124.87	0.200	65+
Ischemic heart disease	12,246	130.76	0.149	65+
Thyroid cancer	12,525	134.68	0.168	65+
Gallbladder cancer	12,743	144.71	0.152	65+
Non-Hodgkin lymphoma	12,963	147.67	0.235	65+
Opioid use	13,137	195.72	0.154	0-14
Uterine cancer	13,598	158.42	0.163	65+
Genital prolapse	14,141	218.66	0.131	65+
Bladder cancer	15,592	187.47	0.185	65+
Breast cancer	15,738	187.30	0.159	65+
Multiple sclerosis	15,939	222.22	0.204	65+
Ovarian cancer	15,964	191.90	0.164	65+
Lung cancer	16,055	180.44	0.145	65+
Melanoma	16,060	210.08	0.123	65+
Pancreatic cancer	16,263	183.18	0.133	65+
Brain cancer	16,621	195.86	0.129	65+
Prostate cancer	17,001	217.05	0.134	65+
Vascular intestinal disorders	17,360	201.29	0.104	65+
Kidney cancers	17,462	211.07	0.163	65+
Colorectal cancer	17,574	208.15	0.149	65+
Peripheral vascular disease	17,637	252.78	0.131	65+
Aortic aneurysm	17,743	228.54	0.173	65+
Parkinson's disease	18,016	245.17	0.218	65+

Myeloma	19,449	244.20	0.153	65+
Atrial fibrillation	20,996	314.69	0.151	65+
Alzheimer's disease	21,922	359.95	0.185	65+