

A SYSTEM SIMULATION MODEL FOR TYPE 2 DIABETES IN
THE SASKATOON HEALTH REGION

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By

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ABSTRACT

Diabetes mellitus is a prevailing chronic disease in Canada and around the world. The population with diabetes is rapidly increasing. The growth of diabetes prevalence places a heavy burden on the health care system and causes a significant loss to society. The prevention and treatment of diabetes is a complex problem that involves many parties such as government, health care system, communities and patients. It is very difficult to design cost-effective interventions that will suit all parties to slow the prevalence of diabetes.

The diabetes-related burden, such as diabetes prevalence and incidence, in the Saskatoon Health Region were investigated by using the System Dynamics approach. A System Dynamics model was built based on the current diabetes situation of the Saskatoon Health Region. The model is able to simulate the entire disease progress as a dynamic system and to catch the interactions and feedbacks between factors. According to the simulation result, the diabetes prevalence and the number of incident cases will continue to increase in the next four decades.

The model is able to help the decision-makers to observe the future impacts of current interventions and find bottlenecks, as well as key uncertainties. The model has the capability to answer many “what-if” and “why” questions. The decision-makers can use the model as a useful tool to evaluate different interventions by performing different experimental scenarios.

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CONTENTS

PERMISSION TO USE.....	i
ABSTRACT.....	ii
ACKNOWLEDGEMENTS.....	iii
CONTENTS.....	iv
LIST OF TABLES.....	vi
LIST OF FIGURES.....	vii
LIST of ABBREVIATIONS.....	x
CHAPTER 1 INTRODUCTION.....	1
1.1 Problem and Motivation.....	1
1.2 Solution and Goal.....	3
CHAPTER 2 BACKGROUND AND RELATED RESEARCH.....	7
2.1 Diabetes Mellitus.....	7
2.1.1 Classification.....	7
2.1.2 Pathophysiology.....	9
2.1.3 Symptoms and Diagnosis.....	11
2.1.4 Complication.....	12
2.1.5 Local Prevalence.....	13
2.2 Health Related Quality of Life (HRQoL).....	16
2.3 System Dynamics Approach.....	17
2.3.1 Dynamic Behavior of Complex System.....	18
2.3.2 System Dynamics Model Structure.....	19
2.3.3 System Dynamics Modeling software.....	21
2.4 Summary.....	23
CHAPTER 3 RELATED RESEARCH AND MAJOR DATA SOURCES.....	24
3.1 System Dynamics Applications in the Public Health Area.....	24
3.2 Major Data Sources.....	31
3.2.1 Local Health Authority Reports.....	31
3.2.2 Statistical Surveys and Census.....	32
3.2.3 Related Research.....	33
3.3 Summary.....	34
CHAPTER 4 SIMULATION MODEL FOR DIABETES IN SASKATOON HEALTH REGION.....	35
4.1 Development of the System Dynamics Model.....	35
4.1.1 Adaption of the New Zealand Model and the CDC model.....	35
4.1.2 Structure Modification and Correction.....	37
4.2 Model Structure.....	40
4.2.1 Normoglycemic Population Section.....	42
4.2.2 Hyperglycemic Population Section.....	54

4.3 Summary.....	84
CHAPTER 5 CALIBRATION	86
5.1 Basic about Calibration	86
5.2 Calibration Structure.....	90
5.2.1 Discrepancy Calculation	90
5.2.2 List of Constant Parameters	96
5.3 Findings	98
5.4 Summary.....	102
CHAPTER 6 RESULTS	104
6.1 Simulation Results.....	104
6.2 Limitation	112
6.3 Summary.....	113
CHAPTER 7 SENSITIVITY ANALYSIS AND INTERVENTIONS.....	115
7.1 Sensitivity Analysis	115
7.1.1 Single-variable Sensitivity Analysis	116
7.1.2 Multi-variable Sensitivity Analysis.....	138
7.2 Potential Interventions.....	150
7.2.1 Interventions for Normoglycemic Population.....	150
7.2.2 Interventions Involving the Hyperglycemic Population	151
7.2.3 Discussion	154
7.3 Summary.....	155
CHAPTER 8 CONCLUSION.....	158
8.1 Thesis Summary	158
8.1.1 Model Construction.....	158
8.1.2 Model Calibration	159
8.1.3 Model Results.....	159
8.1.4 Sensitivity Analysis and Interventions.....	160
8.2 Contribution.....	161
8.3 Future Work.....	163
REFERENCE.....	165
APPENDIX A: STOCK INITIAL VALUES	175
APPENDIX B: MODEL PARAMETER VALUES.....	185

LIST OF TABLES

Table 2-1. Criteria for the Diagnosis of Diabetes Mellitus.....	9
Table 2-2. Diabetes Incidence Rates (per 1000 person) for Aboriginal and Non-Aboriginal Population in Saskatchewan	14
Table 2-3. Age-Sex Adjusted Prevalence Rate in SHR and Saskatchewan	14
Table 5-1. Parameters in Calibration List.....	97
Table 7-1. Variable Combinations for Multi-variable Sensitivity Analysis	139

LIST OF FIGURES

Figure 1-1. Estimated Population Percent Change for Saskatoon Health Region in Year 2005	3
Figure 2-1. Saskatoon Health Region Population Pyramid	15
Figure 2-2. Comparison of Health Related Quality of Life (HUI3) between General Population and Diabetic Population in Canada.....	16
Figure 2-3. Feedback Loops	19
Figure 2-4. Stock and Flow Diagram.....	20
Figure 2-5. Population Groups without Subscript Structure vs. with Subscript Structure	22
Figure 3-1. System Costs for Diabetes	26
Figure 3-2. Concept of Diabetes Progress	30
Figure 4-1. Diabetes Onset and Progress Structure in the CDC Model.....	37
Figure 4-2. General Population Structure in the New Zealand Model	37
Figure 4-3. Incidence Rate of Type 2 Diabetes in Saskatchewan.....	43
Figure 4-4. Normoglycemic Population Aging Chain Structure	44
Figure 4-5. Normal Weight Population Stock and Flows.....	45
Figure 4-6. Overweight Population Stock and Flows.....	49
Figure 4-7. Obese Population Stock and Flows.....	54
Figure 4-8. Development of Hyperglycemia	55
Figure 5-1. Conceptual Structure of Calibration Process	89
Figure 5-2. Calibration Structure for the total population in the SHR.....	92
Figure 5-3a. Comparison of Total Population	98
Figure 5-3b. Comparison of Diabetes Prevalence Rate for RI 55-59 Age Group	98
Figure 5-4a. Comparison of Diabetes Incidence Rate for RI 25-29 Age Group	99
Figure 5-4b. Comparison of Diabetes Incidence Rate for non-RI 25-29 Age Group.....	99
Figure 6-1. Total Population.....	105

Figure 6-2a. Total Diabetic Population.....	106
Figure 6-2b. Total Diabetic Population by ethnic and Gender Groups	106
Figure 6-3. Comparison of Total Obese Normoglycemic, Prediabetic and Diabetic Population	107
Figure 6-4. Diabetes Prevalence by Ethnic and Gender Groups	108
Figure 6-5. Comparison between Age 25 and Age 65 Population Groups.....	109
Figure 6-6a. Total Incident Cases	110
Figure 6-6b. Total Incident Cases in RI population.....	110
Figure 6-6c. Total Incident Cases by Gender Groups.....	111
Figure 6-6d. Total Incident Cases in Elderly Age Group	111
Figure 7-1. Sensitivity Results for Prediabetes Diagnosis Rate	117
Figure 7-2. Sensitivity Results for Diabetes Diagnosis Rate.....	118
Figure 7-3. Sensitivity Results for Overweight Incidence Rate	120
Figure 7-4. Sensitivity Results for Obesity Incidence Rate.....	121
Figure 7-5. Sensitivity Results for Developing Prediabetes from Obese Population Incidence Rate	123
Figure 7-6. Sensitivity Results for Average Years to Develop Diabetes from Undiagnosed Prediabetes	124
Figure 7-7. Sensitivity Results for Average Years to Develop Diabetes from Diagnosed Prediabetes	126
Figure 7-8. Sensitivity Results for Average Years to Develop Early Stage Complication from Undiagnosed Diabetes	127
Figure7-9. Sensitivity Results for Average Years to Develop Early Stage Complication from Diagnosed Diabetes	129
Figure 7-10. Sensitivity Results for Prediabetes Recovery Rate	131
Figure 7-11. Sensitivity Results for Diagnosed Prediabetes Mortality Rate	132
Figure 7-12. Sensitivity Results for Mortality Rate of Diagnosed Diabetes without Complication	133

Figure 7-13. Sensitivity Results for Mortality Rate of Diagnosed Diabetes with Early Stage Complication.....	135
Figure 7-14. Sensitivity Results for Mortality Rate of Diagnosed Diabetes with Late Stage Complication.....	136
Figure 7-15. Sensitivity Results for SHR Birth Rate of Aboriginal Population.....	137
Figure 7-16. Sensitivity Results for Overweight Incidence Rate and Obesity Incidence Rate	140
Figure 7-17. Sensitivity Results for Prediabetes Diagnosis Rate and Diabetes Diagnosis Rate	142
Figure 7-18. Sensitivity Results for Average Years to Develop Diabetes from Undiagnosed Prediabetes and Average Years to Develop Diabetes from Diagnosed Prediabetes	143
Figure 7-19. Sensitivity Results for Develop Prediabetes from Obese Incidence Rate and Prediabetes Diagnosis Rate.....	145
Figure 7-20. Sensitivity Results for Average Years to Develop Early Stage Complication from Diagnosed Diabetes and Mortality Rate of Diagnosed Diabetes without Complication	146
Figure 7-21. Sensitivity Results for Mortality Rate of Diagnosed Diabetes with Early Stage Complication and Mortality Rate of Diagnosed Diabetes with Late Stage Complication.....	148
Figure 7-22. Sensitivity Results for Prediabetes Diagnosis Rate, Prediabetes Recovery Rate and the Average Years to Develop Diabetes from Diagnosed Prediabetes.....	149
Figure 7-23. Changes in Diabetes Burdens from Lowering Overweight Incidence Rate and Obese Incidence Rate Fivefold	151
Figure 7-24. Changes in Diabetes Burdens from Doubling Average Years to Develop Diabetes from Diagnosed Prediabetes and Undiagnosed Prediabetes	152
Figure 7-25. Changes in Diabetes Burdens from Lowering Developing Prediabetes from Obese Population Incidence Rate Fivefold and Rising Prediabetes Diagnosis Rate Fivefold	154

LIST OF ABBREVIATIONS

RI	Registered Indian
NDSS	National Diabetes Surveillance System
SHR	Saskatoon Health Region
CDC	United States Centers of Disease Control and Prevention
WHO	World Health Organization
IDDM	insulin-dependant diabetes mellitus
NIDDM	non-insulin-dependant diabetes mellitus
GDM	gestational diabetes mellitus
MRDM	malnutrition-related diabetes mellitus
IGT	impaired glucose tolerance.
FPGT	fasting plasma glucose test
OGTT	oral glucose tolerance test
IFG	impaired fasting glucose
HRQoL	health related quality of life
CCHS	Canadian Community Health Survey
HUI3	Health Utilities Index Mark 3
QALY	Quality-Adjusted Life-Year
NPHS	National Population Health Survey
AMI	acute myocardial infarction
SA	sensitivity analysis

CHAPTER 1

INTRODUCTION

Diabetes Mellitus, colloquially referred as “diabetes”, is a chronic syndrome that results from insufficient secretion or inefficient use of insulin. The disease significantly reduces patients’ overall wellness and quality of life, and leads to a broad set of serious complications. Society also is impacted negatively from loss of productivity and heavy burden on public health care system.

My research proposes to develop a System Dynamic model that simulates Type 2 diabetes burdens such as the incidence and the prevalence of Type 2 diabetes in the Saskatoon Health Region. The model will be used to better understand the population-wide progression of Type 2 diabetes as a complex system, predict future prevalence and other burdens of Type 2 diabetes and evaluate possible interventions. My research focuses on understanding the population-level impact of diabetes rather than discussing the syndrome at a clinical level.

1.1 Problem and Motivation

The prevalence of Diabetes Mellitus has rapidly increased due to population increase, population aging, urbanization, and increasing prevalence of obesity. An estimated 171 million people suffered from diabetes worldwide in the year 2000; the estimated number grew to more than 180 million in the year 2006. The diabetic population is projected to increase to 366 million by 2030 [1, 2]. In Canada, the prevalence of diabetes is high and rapidly increasing. National Diabetes Surveillance System (NDSS) data estimated that 1.128 million people – about 4.8% of the total 20+ age population – were diagnosed with diabetes during 1998-99. If one factors in the estimate of the undiagnosed diabetics population, there were a total of 1.7 million Canadian with diabetes during 1998-99 [3, 4]. A recent report from the NDSS shows that the prevalence of diagnosed diabetes increased to approximately 1.783 million in the year 2004-05 [5]. The prevalence including undiagnosed diabetics increased to more than 2 million and is expected to rise to 3 million by the end of the decade [4, 6].

The prevalence of diabetes places a heavy burden on diabetic patients, the health care system, and society. Diabetic patients not only physically suffer from diabetic complications, but also economically suffer from medical and day-to-day care expense. Diabetes also is a costly disease socially since it consumes a large portion of health care resources. It directly adds additional physician service costs, hospital service costs, long-term care costs, medication costs, laboratory costs and other therapy and management costs to the health care system and society. If indirect costs are counted in, the number will be twofold to threefold more than the direct costs. Diabetes led health spending costs by imposing \$884 million of direct health care costs in 2000 in Canada; and indirect costs from lost productivity and premature death imposed another \$1.7 billion in costs to the Canadian economy [7].

Saskatoon is not an exception to Canadian's high diabetes prevalence. Diabetes is the chronic disease with the third highest mortality burden in the Saskatoon Health Region (SHR) demographically. Obesity is a well-known risk factor of developing Type 2 diabetes. A high prevalence of obesity in the Saskatoon Health Region makes a considerable contribution to the high diabetes prevalence. The cold winters in Saskatchewan restrict outdoor physical activities and limited recreation facilities restrict indoor physical activities. Many urban residents also find it difficult and costly to access healthier food. Many people in the Saskatoon Health Region are overweight or obese. A total of 30.63% of the residents in the Saskatoon Health Region were overweight and 16.88% were obese in 2005 [8]. Partly as the consequence of the high prevalence of obesity, diabetes is also prevalent in the Saskatoon Health Region.

In addition to the prevalence of obesity, the increase in diabetes burden also results from population structure. The populations of the younger groups in the health region are continuously decreasing or remain stable; at the same time, the populations of the older groups keep increase as shows in Figure 1-1. Chronic diseases like diabetes, which commonly onset at older age, are prevalent in the elderly populations.

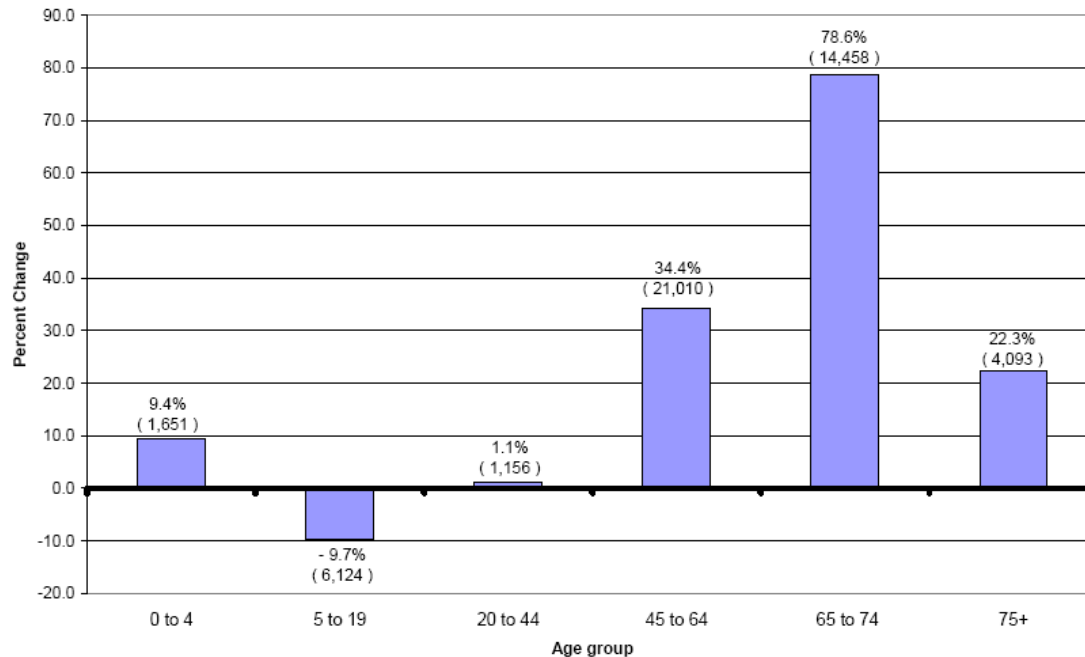


Figure 1-1. Estimated Population Percent Change for Saskatoon Health Region in Year 2005

Aboriginal people are the higher risk ethnic group for having diabetes in North America [68-69]. About 8.7% of the population of the Saskatoon Health Region are aboriginal, and over 50% of those are Status Indians based on Statistics Canada 2001 data. This relatively large percentage of aboriginal population when compared to other areas in Canada also contributes to the elevated diabetes prevalence seen in the SHR.

With the limited budget available for preventing and treating diabetes and its complications, cost-effective intervention policies are needed in order to slow the increase of prevalence of diabetes and lower the burdens imposed by diabetes, and save as many lives as possible.

1.2 Solution and Goal

It is not easy to develop the best diabetes intervention plan within a complex environment full with limitations and contradictions. How do we save the most diabetic patients' lives in next year, over the next decade, over the next two decades? How do we minimize the burden imposed by diabetes to diabetic patients, health care system and society? There are many

questions that need to be answered. In this thesis, we are trying to provide potential solutions by using the System Dynamics approach.

The System Dynamics approach, first formulated by Jay W. Forrester in early 1960s, is a computer-aided methodology for understanding, analyzing and managing complex feedback systems [9-11]. Diabetes is a complex social problem rather than a simple medical problem. Any snapshot view will not capture the dynamic relationships within the system and possibly miss potential outcomes. A System Dynamics model is able to create a systems-level view that captures dynamics (changes over time) across the whole system rather than for a piece of the system considered in isolation. It also monitors every interaction between system components and interaction between the system and exogenous factors.

The goal of this research is to develop a System Dynamics model that characterizes the health and demographic structure of diabetes in the Saskatoon Health Region. This model will be used as a learning tool to improve our understanding of the drivers underlying observed and future changes in the diabetes prevalence and incidence, answering questions such as “What are the main contributing factors for the high prevalence of diabetes in SHR? Are they the prevalence of obesity, the population age structure, the population ethnic structure or something else?”. The model also could be used as an evaluation tool to examine the tradeoffs between different interventions and to try to identify the best combination of interventions that will address the SHR’s strategic plans.

Our research involves 5 stages of work:

1. Construct a system dynamics model that accords with the local society and health care system but that draws on elements of two previous models: a model from the United States Centers for Disease Control and Prevention (CDC) and one from New Zealand.

Previously, researchers at the U. S. Centers for Disease Control and Prevention and the New Zealand Ministry of Health developed System Dynamics models for diabetes in the

U. S. and New Zealand, respectively. We adapted the structures from these models, and modified the structure based on features of the local situation. The CDC model and the New Zealand model will be described in the chapter 3, and the adaption process will be described in the chapter 4.

2. Parameterize the model with local data or other data sources.

After the model is constructed, most of parameters in the model are substituted with local values. If some parameters do not have local data available, we use data from other sources instead. These sources includes data for Saskatchewan, data for Canada and data for other countries. In most cases, we do not anticipate that these data will exhibit a large difference from actual local values. The parameterization will be explained in the chapter 4 with model structure.

3. Calibrate the model with historical data and estimate unknown parameters.

In this step, we calibrated and verified model structure and parameters with historical data. Using changes to values of model parameters and structure, we tried to find a best match between model output and the historical data. After the calibration, the model is able to adequately reproduce the historical trace of the diabetes burden within the SHR.

In the calibration process, we also estimated values for unknown parameters in the model. Data on some parameters is difficult to collect data because of their definition, such as undiagnosed diabetic population. We use the simulation software to simultaneously and randomly change the values across unknown parameters within a reasonable range. If a value in a given range leads the model outputs to best match the historical data, then this

value is considered the best estimate for the unknown parameter. The calibration process will be described in the chapter 5.

4. Use the calibrated the model to depict the underlying diabetes burden in the SHR in the near future.

After the model is calibrated, it can simulate the diabetes burdens in the SHR with a reasonable accuracy based on the available information. We use the model to project several important indicators of diabetes burdens. These indicators show the trend of diabetes burdens in the SHR in the near future. The simulation results will be exhibited in the chapter 6.

5. Test sensitivity of selected model variables and test potential interventions

In this step, we tested the sensitivity levels of the system responses to changes in several selected model variables. We alter the values of several key variables in the model and observe the changes in the model results. Changes in some variables may lead to a large change in the model outputs; changes in other variables may lead to a small change.

Based on observations from the sensitivity analysis, we propose several potential interventions. Interventions alter key variables which can to lead changes in the diabetes burdens. The simulation results show that the interventions have the potential to lower the diabetes burden from their original forecast. The sensitivity analysis and its results will be described in chapter 7.

CHAPTER 2

BACKGROUND AND RELATED RESEARCH

2.1 Diabetes Mellitus

Diabetes is a prevalent chronic metabolic disease that affects people regardless of age, gender or race. The basic pathogenesis of diabetes is that the pancreas cannot produce enough insulin, or the insulin cannot be used effectively by body cells. Insulin is the hormone produced by the pancreas to trigger body cells to convert glucose to energy for the human body. When the pancreas cannot produce insulin or cells do not respond to insulin, the blood glucose level raises. Constant high levels of glucose in the bloodstream damage blood vessels, kidney, nerves, heart and result in many chronic complications; such as retinopathy, neuropathy and nephropathy.

2.1.1 Classification

Diabetes is groups of metabolic disorders that are characterized by hyperglycemia resulting from defects on insulin secretion, insulin action or both [12, 13]. There are guidelines that provide an appropriate classification system to identify various forms and stages of diabetes. The classification, published by World Health Organization (WHO) in 1980, is the first classification that has been widely accepted and used by professionals and the general public. This classification was based on the classification system that the National Diabetes Data Groups developed and published in 1979 [13-16].

Diabetes is divided into five major types based on clinical and etiological features in the WHO 1980 classification and its 1985 revision [13-17]. The first two primary types are insulin-dependent diabetes mellitus (IDDM or Type 1 diabetes), and non-insulin-dependent diabetes mellitus (NIDDM or Type 2 diabetes). Beside the first two major types, there are several other types of diabetes that have different etiological character, such as diabetes induced through pancreatic disease, disease of hormonal etiology, drug- or chemical-induced conditions, insulin receptor abnormalities and certain genetic syndromes. They are grouped in the “other

types of diabetes” class. Gestational diabetes mellitus (GDM) was in this classification as a temporary high blood glucose level condition during pregnancy. Malnutrition-related diabetes mellitus (MRDM) was not defined in the original 1980’s classification, but it was recognized as the fifth major type in the WHO classification’s 1985 revision.

Impaired glucose tolerance (IGT) was also defined in the 1980’s version of classification as an intermediate stage for people who have hyperglycemia but blood glucose levels are not sufficiently elevated to meet diabetes requirement.

With the growth of knowledge and understanding about diabetes, the 1980’s classification is no longer able to fill the requirement of classifying diabetes precisely. An international diabetes experts committee among the World Health Organization and the American Diabetes Association released a revised classification based on etiology in 1997. In the new classification, diabetes has been divided into four major classes: Type 1 diabetes, Type 2 diabetes, other specific types and gestational diabetes. The terms “insulin-dependent diabetes mellitus” and “non-insulin-dependent diabetes mellitus” are eliminated since these terms classified patient based on treatment rather than etiology [13]. The term “Type 1 diabetes” replaced the old term “insulin-dependent diabetes mellitus” and the acronym “IDDM” to classify diabetes that results from β -cell destruction. The term “Type 2 diabetes” replaced the term “non-insulin-dependent diabetes mellitus” and the acronym “NIDDM” to classify diabetes that results from insulin resistance. The “other specific types” class includes many other types diabetes which are caused by different factors. The class “gestational diabetes mellitus” retains the same as the previous classification.

Table 2-1. Criteria for the Diagnosis of Diabetes Mellitus

- | |
|---|
| <p>1. Symptoms of diabetes plus casual plasma glucose concentration ≥ 200 mg/dl (11.1 mmol/l). “Casual” is defined as any time of day without regard to time since last meal. The classic symptoms of diabetes include polyuria, polydipsia, and unexplained weight loss.</p> <p>or</p> <p>2. Fasting Plasma Glucose (FPG) ≥ 126 mg/dl (7.0 mmol/l). “Fasting” is defined as no caloric intake for at least 8 hour.</p> <p>or</p> <p>3. 2-hour PG ≥ 200mg/dl (11.1 mmol/l) during an Oral Glucose Tolerance Test (OGTT). The test should be performed as described by the WHO, using a glucose load containing the equivalent of 75 g anhydrous glucose dissolved in water.</p> |
|---|

Table 2-1 lists the criteria for the diagnosis of diabetes. In its 1997 classification, the international diabetes experts committee also defined two intermediate stages, impaired glucose tolerance (IGT) and impaired fasting glucose (IFG). The intermediate stages are commonly referred as prediabetes since they have higher level of glucose than normoglycemia but lower than the glucose levels used in the criteria for diabetes diagnosis.

2.1.2 Pathophysiology

Type 1 diabetes (previously known as insulin-dependent diabetes mellitus) is characterized by destruction of pancreatic β -cells and not enough or no insulin being produced by the pancreas. Type 1 diabetes is known not to be caused by unhealthy diets or lifestyle but by combinations of genetic and environmental factors. After a person eats, islet cells in the pancreas secrete insulin to signal insulin-sensitive tissues. An immunological deficiency causes pancreatic β -cells in islets to be totally destroyed or sufficiently damaged by the immune system, thereby extinguishing the production of insulin.

The onset of Type 1 diabetes usually occurs in childhood or adolescence. The incidence rate of Type 1 diabetes varies with age, but it peaks at about 11-13 years of age [18]. At the same time, epidemiological data shows about 30-50% cases develop Type 1 diabetes symptoms after age 20 [19-21]. About 10% of the total Canadian diabetic population are Type 1 [3, 4, 22], and the fraction is decreasing due to the rising prevalence of Type 2 diabetes.

The remaining 90% of diabetes cases are associated with Type 2 diabetes, which used to be termed non-insulin-dependent diabetes mellitus (NIDDM). Type 2 diabetes is characterized by abnormalities in both insulin secretion and insulin action. Insulin resistance is a well known major driver of hyperglycemia of Type 2 diabetes. Defects in insulin receptors in cells and postreceptors in organs cause insulin-sensitive tissues in a diabetic patient's body that do not respond to normal level of insulin and refuse to absorb glucose. Insulin resistance lowers glucose disposal in skeletal muscle and speeds up endogenous glucose production in the liver. Both actions result in hyperglycemia of Type 2 diabetes.

A defect in insulin secretion is another driver of hyperglycemia in Type 2 diabetes. Studies carried out in humans of varying ethnicity (Caucasians, Native American Indians, Mexican-Americans) and Rhesus monkeys indicate that Type 2 diabetes patients have a progressive decline in insulin secretion when plasma glucose level exceeds 120 to 140 mg%; and the level of circulating insulin diminishes (insulinopenic) when the plasma glucose level exceeds 180 to 200 mg% [23].

Type 2 diabetes is highly associated with obesity and physical inactivity. Obesity greatly increases the risk of developing Type 2 diabetes. Being overweight and gaining weight are strong predictor of diabetes [24-26]. Studies show obese middle age and elderly males (from age 40 to 75) whose body mass index (BMI) $\geq 35 \text{ kg/m}^2$ have a multivariate relative risk of 42.1 in 5 years compared to male whose BMI $< 23 \text{ kg/m}^2$ [27]. Another study documented that age adjusted cumulative incidence of diabetes is 26.2% for people BMI > 37 compared to 9.6% for people with BMI < 29 [24]. It is expected that the current prevalence of obesity will lead to a high prevalence of diabetes in the future. Studies have suggested that for every 1 kg

increase in population-measured body weight, the prevalence of diabetes increases by 5% to 10 % [3, 25, 26].

Gestational diabetes mellitus (GDM) is a temporary glucose intolerance that happens during pregnancy. Gestational diabetes usually does not have obvious symptoms, hence it only can be detected by screening. GDM increases the risk of prenatal deaths for mothers slightly, and the risk of prenatal death for baby by about 3 times compared to the general population [28]. Babies whose mothers have GDM during pregnancy sometimes are heavier and larger than normal babies. These babies are called macrosomic and have a disproportionately high fat content; and caesarean section is most likely needed for delivery.

Even though most gestational diabetic patients will revert to normoglycemia after delivery, GDM is a strong risk factor for both mother and baby to develop Type 2 diabetes in their later life stage. Women who have gestational diabetes will have 20% to 50% chance of developing Type 2 diabetes in next 5 to 10 years [22]. Babies who have a diabetic mother suffer from a higher diabetes incidence rate with a prevalence of 1.5% at 25 years [28], and this prevalence is far higher in certain Aboriginal groups [68].

Type 1 diabetes is related to genetic and environment factors. It is therefore hard to develop a feasible intervention to slow down prevalence in a relatively short term. Moreover, Type 1 diabetes only represents about 10% of the total diabetic population, and a much smaller fraction of diabetics among the rapidly-growing Aboriginal subpopulation. In my research, I only focus on Type 2 diabetes.

2.1.3 Symptoms and Diagnosis

Type 2 diabetes is not easy to symptomatically diagnose since the onset is a slow process after patients are exposed to elevated levels of blood glucose for a long time period. Not all people with diabetes are diagnosed immediately, because at the early stage, diabetes usually has no obvious symptom and the disease may not be diagnosed. Prediabetes, the intermediate stages between normoglycemia and diabetes, usually does not have any obvious signs or symptom. Plus, the symptoms of early stage Type 2 diabetes seem harmless such as frequent

urination, extreme hunger and thirst, rapid weight loss and blurry vision. The mildness of such symptoms places additional barriers to the diagnosis of Type 2 diabetes in the early stage. According to the National Diabetes Surveillance System (NDSS) 1998/99 data, an estimated 1.128 million Canadians were diagnosed with diabetes [3]. However, this number does not include all diabetes cases in Canada. It has been estimated about one third of diabetes instances are not diagnosed [29, 30]. In 2006, the Centers for Disease Control and Prevention (CDC) estimated that 6.2 million people in the United States have undiagnosed diabetes among a total of 20.8 million diabetics [22].

People with undiagnosed diabetes may not be seen as suffering from diabetes-imposed burdens, but those people are usually obese and have other symptoms such as high blood pressure. The progression of diabetes for unmanaged diabetic patients can be much quicker than for well managed patients, and causes an even heavier burden later.

The World Health Organization published its revised recommendation on diabetes diagnosis criterion in the WHO diabetes classification, as shown in Table 2-1 [12, 13]. This criterion also defines an intermediate level of glucose, which does not meet the diabetes level but is higher than normal level. People who have FPG levels ≥ 110 mg/dl (7.0 mmol/l) but < 126 mg/dl (7.0 mmol/l) or 2 hour OGTT value ≥ 140 mg/dl (7.8 mmol/l) but < 200 mg/dl (11.1 mmol/l) are considered “prediabetic”. Based on the WHO recommendation, a patient is diagnosed with diabetes if a positive result is given from any of three methods shown in Table 2-1, and this positive result must be confirmed on a subsequent day by any one of these three methods.

2.1.4 Complications

Diabetic complications are the foremost causes of mortality in diabetic patients. Preventing and slowing the progression of diabetic complications are the keys saving diabetic patients’ lives. If diabetes is not diagnosed at the early stage and blood glucose levels remain unmanaged, the development of chronic complications can be accelerated. These long-term complications, such as cardiovascular diseases, high blood pressure, nephropathies (kidney

diseases), neuropathies (nervous system disorders) and retinopathies (eye diseases), impose a huge amount of illness to diabetic patients and can greatly compromise their quality of life.

Diabetes was the main cause for nearly 45% kidney failure cases in the United States in 2005 [31]. Diabetes related kidney failure usually takes 13 to 16 years to develop and can be extremely expensive once it occurs. However, with good care and management, kidney disease can be prevented or slowed. Retinopathy is another serious complication that results from diabetes. High levels of blood glucose damage the blood vessels in the retina and cause vision loss or even blindness. About 40% to 45% diabetics in the United State are affected by retinopathy [32]. Beside nephropathy and retinopathy, other chronic diabetic complications also lead to serious organ failure, and even death. Diabetic complications will commonly shorten the average life span and significantly reduce quality of life among diabetic patients.

2.1.5 Local Prevalence

Saskatoon Health Region is the largest health region in Saskatchewan. It services 285,000 people (approximately 28.5% of the provincial population) in 2 cities; 69 towns, villages and hamlets; 47 whole or partial rural municipalities; and 6 First Nations reserves [8].

A considerable fraction of the population in Saskatoon Health Region (SHR) is overweight or obese. 59.7% of the age 18+ male population and 41.3% of the age 18+ female population in the SHR were reported overweight or obese in 2001[33]. This large high risk population could have a significant effect on future diabetes prevalence.

Not only obesity but also an aging population structure in the SHR has a major contribution on developing Type 2 diabetes. Figure 2-1 illustrates the population age structure in SHR; a large percentage of the population in the SHR is elderly: 12.6% of the city population and 15.5% of the rural population in the Health Region are over the age of 65 [8]. When considered for the SHR as a whole, the population of older age groups continuously increases and the population of younger age groups keep stable or slightly decrease. As for obesity, age also makes substantial contributions to the risk of Type 2 diabetes. People who are older than

age 45 have higher risk of developing Type 2 diabetes than younger people. Combining both obesity and age, it is not surprising that diabetes is prevalent in the SHR.

As the largest health region in the province, SHR covers about a quarter of diabetes patients in Saskatchewan. Compared to other health region in the province, prevalence rate of diabetes in SHR is relatively lower. The incidence rates vary from year to year with statistical noise, but the Aboriginal population has a significantly higher incidence rate than the non-Aboriginal population. The incidence rates for Aboriginal and non-Aboriginal population in Saskatchewan, which are very close to the rates for the populations in the SHR, are shown in Table 2-2 [69]. Even though the incidence rate decreases, new cases still develop every year and results in an increases in the prevalence rate as shown in Table 2-3 [34].

Table 2-2. Diabetes Incidence Rates (per 1000 person) for Aboriginal and Non-Aboriginal Population in Saskatchewan

Year	Non-Aboriginal Male	Non-Aboriginal Female	Aboriginal Male	Aboriginal Female
1999	5.86	4.46	17.08	19.10
2000	5.99	4.92	16.38	19.57
2001	6.62	4.99	16.28	19.96
2002	7.26	5.42	17.73	18.06
2003	6.77	5.29	17.80	17.95

Table 2-3. Age-Sex Adjusted Prevalence Rate in SHR and Saskatchewan

Year	00-01	01-02	02-03	03-04
Saskatoon Health Region	4.3	4.7	5.1	5.4
Provincial	4.8	5.2	5.6	6.0

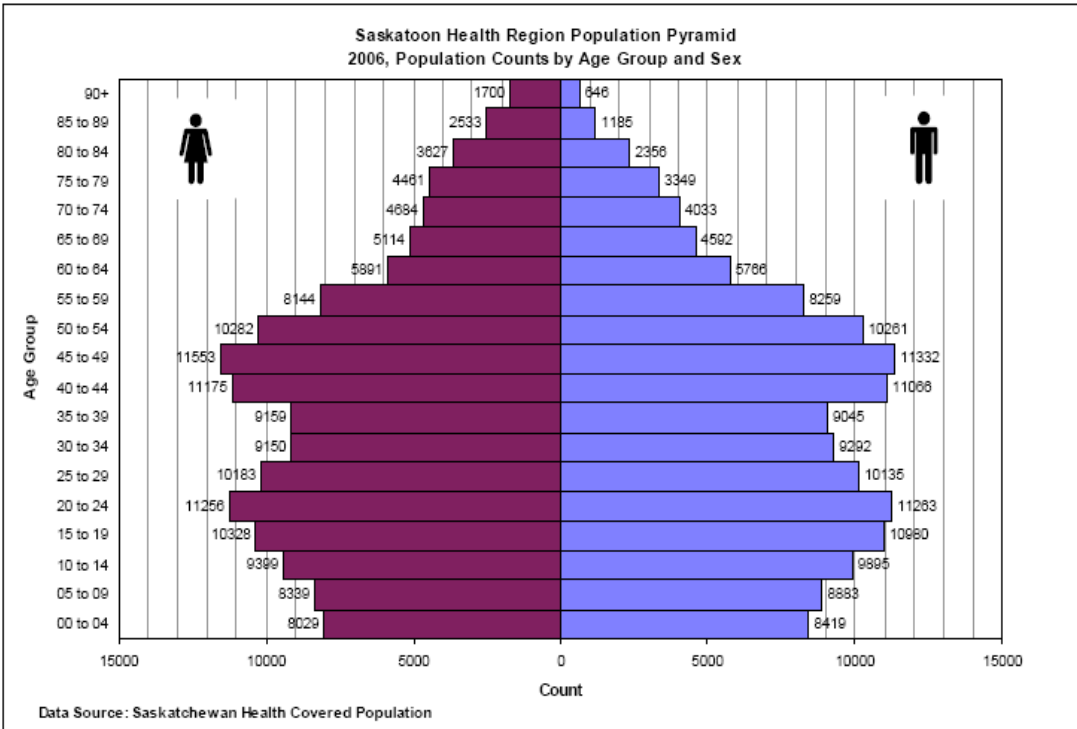


Figure 2-1. Saskatoon Health Region Population Pyramid (taken from [8])

A total of 286,314 people in the SHR and 15,805 people self-identified as having Registered Indian Status (RIS) according to SHR data [61]. Unlike the overall population structure, the age structure for the Aboriginal population is young. About 48% of the Aboriginal population is under age 20 [35]. On the other hand, the prevalence of diabetes is higher in the Aboriginal population than others. Many surveys result, including the Aboriginal People Survey (APS), the First Nations and Inuit Regional Health Survey (FNIRHS) and First Nations Regional Longitudinal Health Survey (RHS), indicated that diabetes prevalence among the Aboriginal population is 3 to 5 times higher than for the general Canadian population [36, 37].

2.2 Health Related Quality of Life (HRQoL)

Diabetes not only physically damages the human body, but also mentally and economically destroys people's life. People with diabetes often feel that they are challenged by the disease and day-to-day disease management [40]. Health related quality of life is an important component and indicator in the measurement of quality of life [38, 39]. Health related quality of life is a multi-dimensional factor that takes into account people's physical and mental health, and health related social and economic well-being [40]. An improvement of health related quality of life means improvements in physical as well as mental health well-being. Hence, the improvement of health related quality of life can be used to evaluate the effectiveness of health programs or policies.

Health related quality of life is significantly reduced by diabetes. Results from the Canadian Community Health Survey (CCHS) shown in Figure 2-2 suggests that the health related quality of life for diabetic population is lower than the health related quality of life for the general population across all age groups and genders. An effective diabetes intervention should not only slow the prevention, and lower diabetes related burden in terms of extending the length of life, but also improves health related quality of life for diabetics.

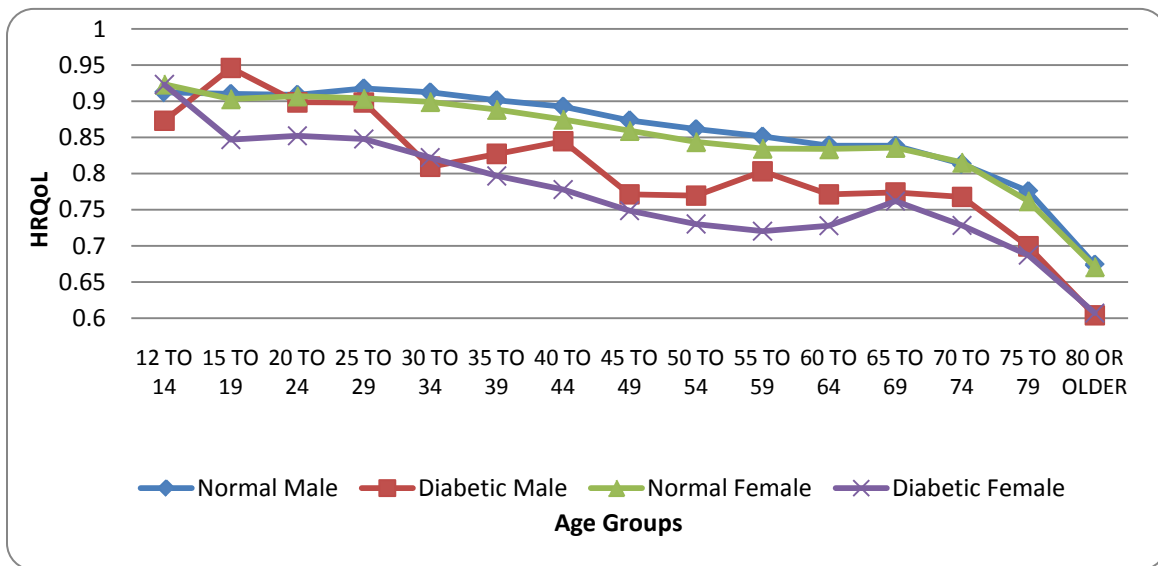


Figure 2-2. Comparison of Health Related Quality of Life (HUI3) between General Population and Diabetic Population in Canada (Calculated from CCHS data)

2.3 System Dynamics Approach

The System Dynamics approach – originally called industrial dynamics – is a computer-aided methodology for analyzing and managing complex feedback system [9, 10]. Since it was formulated by Jay W. Forrester in the early 60s, System Dynamics methodology focuses on complex social, physical, and biological issues [41]. A well built System Dynamics model is able to systemically represent a complex problem in terms of a set of interacting feedback systems. By observing interactions within and between these feedback systems, users of the System Dynamics model tool can identify key factors in the complex problem and gain a better understanding of the problem. A System Dynamics model can be used as simulator to answer “what-if” questions. Decision makers will be able to examine expensive interventions without the needs to actual undertake the interventions. A System Dynamics model can simulate interventions, project possible outcomes and assist decision makers in creating the most effective intervention. A System Dynamics model also can be used as a learning tool to deliver detailed information about the complex problems to researchers and to the general public.

The health of the population, the health care and public health systems is a complex feedback system that involves many factors in diverse areas. The factors in the system are linked and affect each other nonlinearly in either positive or negative ways. For instance, additional primary health care resources for diabetes could save lives from the complications of diabetes; but this requires additional financial resources and human resources that may cause a burden on other areas, and will also elevate the prevalence of diabetes. Moreover, diabetes is a chronic disease, and any political intervention to it will take long time to show results. For example, school-based physical activity or nutrition programs will not have an immediately effect on saving patients’ lives, but it will show its contributions on slowing the prevalence of diabetes over the course of decades. Consequently, diabetes must be viewed as a complex social problem rather than as a simple medical problem. A snapshot view will not capture the dynamic relationships within the system and is likely to miss possible outcomes. The System Dynamics approach offers a useful analysis tool for understanding and studying diabetes.

2.3.1 Dynamic Behavior of Complex System

A complex system is composed of many components. The components in the system are often tightly coupled and interact with each other to form dynamic behaviors of the system. The complexity of the system results not only from its complex structures and components, but also from the many aspects of the system such as the interactions between components in the system, time delays between taking a decision and its effects, and the history of the system.

The interactions between components commonly form what are called feedbacks in System Dynamics studies. Such feedback underlies much of the complex behaviors in the system, including system stability, rapid changes and instability, oscillation, and other frequent phenomena. There are only two types of feedback loops: positive and negative feedback loop are shown in Figure 2-3 as a causal loop diagram. The left loop that labeled “R” is a positive feedback loop or self-reinforcing loop. A change in a certain direction within a positive feedback loop will lead to a cascading set of changes that will ripple around and amplify the original changes. This new change can trigger a similar amplification. An example of the instability and rapid changes from a positive feedback loop can be observed commonly from the volume rapid increase when a microphone is placed close to a speaker. The positive feedback loop in Figure 2-3 will finally result both new born babies and total population growing exponentially if we ignore the other loop.

The right loop in Figure 2-3 that labeled “B” is a negative feedback loop or self-balancing loop. A change in a certain direction within a negative feedback back will lead to a cascading set of changes as “resistance force” that will push back the original changes. The negative feedback loop tends to “self-regulate” deviation and stability. A real life example can be observed from a driving car: faster the car drives the larger resistance force the car faces. When the resistance force equals the drive force from the engine, the car stay in a homeostasis status and the speed of the car does not change. The negative feedback loop in Figure 2-3 will result in a balance point for both total population and death, which is 0 in both cases, if we ignore the positive feedback loop on the other side.

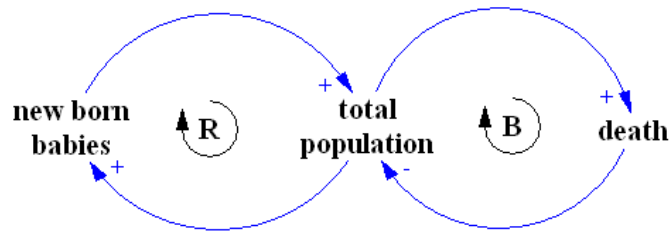


Figure 2-3. Feedback Loops

The existence of only two types of feedback loop does not mean less complexity in a system. In fact, a system could easily have thousands of feedback loops that are nested and interact to create the dynamic behavior of the system.

Time delays between taking a decision and its effects also lead to additional dynamic complexity of systems and create instability in systems [11]. A hot housing market generates considerable new construction sites. The price of a house acts as a feedback that tells developers of the high demand in the housing market. Developers will continuously increase market supply by starting new construction sites in response to the rise in house prices. Developers often will not stop constructions until house prices fall, when it is too late. These new constructions could not stop immediately and will overshoot actual demand; and the oversupply can lead to oscillations in the house prices.

A system is frequently history-dependent since many actions in the system are irreversible or long delays occur between an action and its reverse action [11]. The current state of the system is determined by previous states, and the current state will determine future states of the system. For instance, in the design of city layout, the current layout of the City of Saskatoon is based on the layout decades ago, and it is virtually impossible to change the entire layout in the near future.

2.3.2 System Dynamics Model Structure

Creating an accurate System Dynamics model involves several important steps: identifying the real world problem, identifying relationships between entities, identifying stocks

and flows, writing formulae for particular variables and parameterizing the model with initial values.

In the last section, we showed that the causal loop diagrams using feedback loops to illustrate relationships between entities in a complex system, but it shows little quantitative details of the system. We use stock and flow diagrams to illustrate greater quantitative detail, and use equations that lie behind stock and flow diagrams to simulate the system. Stock and flow on one hand, and feedback on the other hand, are the two central concepts of dynamic system theory [11].

As suggested by its name, a stock and flow diagram uses stocks and flows to characterize a system. Stocks are accumulations of system entities. Stocks collectively characterize the state of a system, and provide the basis for actions, inertia and memory in a system. Stocks also create delays, decouple rates of flows, and break equilibrium in a system. Stocks are variables in a system; flows are rates of changes of these variables. In stock and flow diagrams, stocks are drawn as boxes with a name inside, and flows are presented as pipes with a “valve” symbol. Figure 2-4 is the stock and flow diagram adapted from Figure 2-3. Flows determine the changes of stocks; on the other hand, stocks’ value influence flows as well. The “death” outflow decreases the size of the population. As the population size decreases, the death flow (measured in terms of deaths per unit time – e.g. per year) will drop as well, as there are fewer people at risk of death. Both stocks and flows work together to create dynamics in systems.

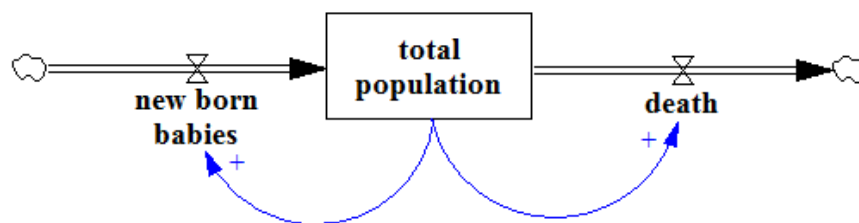


Figure 2-4. Stock and Flow Diagram

Stock and flow diagrams visually present a real life problem in a systems level to people; equations allow for mathematical simulation of the system and produce results behind the scenes. A flow in the model is mathematically presented by formulae. A flow is also a component of the derivatives of the related stock. Each flow is mathematically presented by a parameter in an integral equation, which is for calculation of the size of the stock. Integral Equation 2.1 simulates the inflow (new born babies), outflow (death) and accumulation of the stock (total population) in above stock and flow diagram.

$$total\ population(T) = \int_0^T [new\ born\ babies - death]dt . \tag{2.1}$$

In a large scale model, step by step, hundreds or even thousands of equations work together to simulate a system and calculate results. In the model developed by me, there are 680 stocks and more than 1 thousand flows.

After creating simulation model structure in a stock and flow diagrams and writing equations, we need to collect and apply initial values and constants of the model. Without accurate initial values and constants, the model may not be able to simulate the real world problem and could even produce misleading results.

2.3.3 System Dynamics Modeling Software

Theoretically speaking, it is possible to build a system dynamics model without a system dynamics modeling software. Using Microsoft Excel to write equation also can yield the same results as using a modeling software; then why do we need modeling software?

Modeling software allows developers graphically create a system dynamics model. Using such software, developers can visually construct the model with stocks and connect stocks with flows. Modeling software also allows simulations to run in “slow motion”, and observe changes in the system step by step. Hence, developers can easily locate and track unexpected changes, and identify the causes cross entire simulation period.

In many situations, an entity in a model has many different concepts or has multiple classes. For example, population in a model can be classified into different subgroups according to age, gender or ethnicity based on modeling requirements. However, no matter how many classes an entity has, they all have the same structure and equations in the model since they are under a same umbrella of the entity. Many System Dynamics modeling software provide subscript functionality to use one variable or equation to represent multiple concepts and reduce duplications. Figure 2-5(a) shows the population structure in Figure 2-4 if we classify the total population of western Canada into several different subgroups based on geography: population in British Columbia, Alberta, Saskatchewan and Manitoba. Although population for all provinces has the exactly same structure, modelers still need to draw the same structure and enter equations four times if there is no subscript.

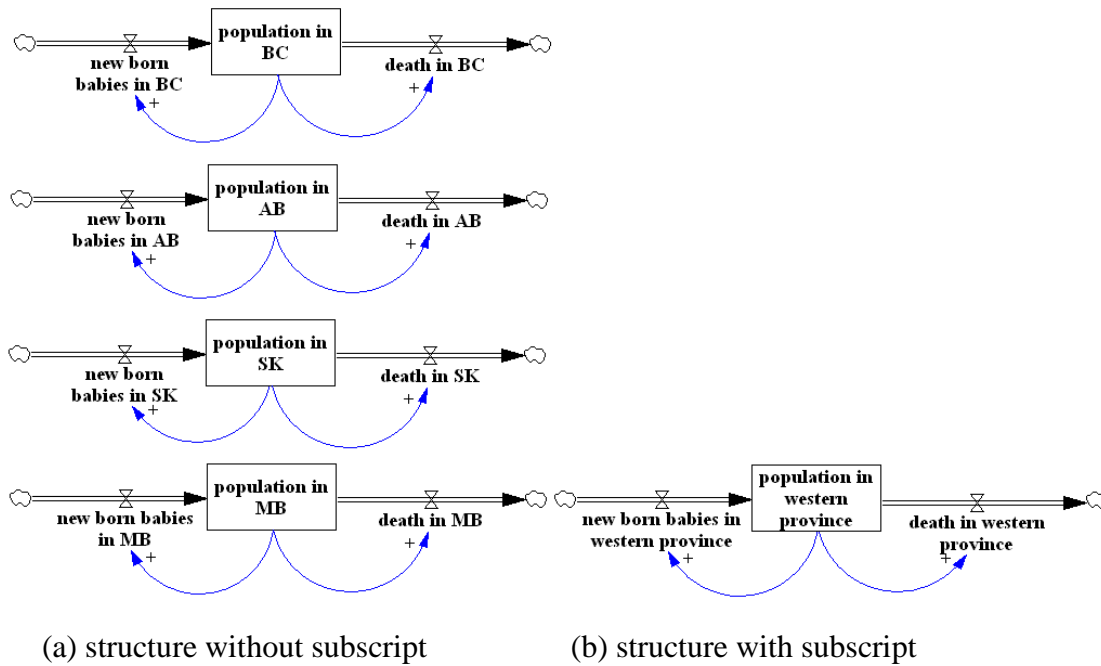


Figure 2-5. Population Groups without Subscript Structure vs. with Subscript Structure

With subscript support, modelers can reuse the same structure and equations for all classes. Figure 2-5(b) shows all population groups can use the same stock and flow diagram,

and Equation 2.2 calculates populations stocks across all provinces using subscripts. Subscripts are heavily applied in my model since many entities are classified into different subclasses. I will describe the subscripts used in my model in chapter 4.

$$\begin{aligned}
 & \text{population in western province}[BC, AB, SK, MB](T) = \\
 & \int_0^T [\text{new born babies in wester province}[BC, AB, SK, MB] - \\
 & \quad \text{death in wester province}[BC, AB, SK, MB]]dt + \\
 & \text{population in western province}[BC, AB, SK, MB](t = 0).
 \end{aligned}
 \tag{2.2}$$

In my research, I selected Vensim as the modeling software. It has a sketch mode that modelers can use to create conceptual causal loop diagrams or stock and flow model structure graphically. Vensim also provides a flexible text based editor that allows experienced developers to create and modify a model in more efficient ways by using mathematical equations directly. The software can be obtained from the official website <http://vensim.com/>.

2.4 Summary

In this chapter, I briefly explained some background information about our research. Diabetes is highly associated with many chronic conditions, including nephropathy and retinopathy, which could destroy people’s life entirely. Nevertheless, with high prevalence of obesity, Type 2 diabetes is prevalent in the SHR population. We are seeking for a tool to gain a better understanding of the local situation, and a potential solution to slow the rise in prevalence. System Dynamics approaches became desirable selection for achieving our goal.

I also explained some foundational concepts about the System Dynamics approach and basic components of a System Dynamics simulation model in this chapter. In the next chapter, I will review some existing research that uses the System Dynamics approach in the public health area. In chapter 4, I will explain our diabetes model in details.

CHAPTER 3

RELATED RESEARCH AND MAJOR DATA SOURCES

Modeling approaches used in public health broadly started from statistical approaches, moved to stochastic and Markov approaches, then into “systems thinking” modeling including System Dynamics modeling and Agent-Based modeling methods. The use of System Dynamics approaches to analyze issues in the public health area is well established. The System Dynamics approach was previously applied to many public health areas such as heart disease, diabetes, HIV/AIDS, cancer, tobacco, etc. In this chapter, I describe some pioneering research in this area, since they provided a solid foundation for my study. I also describe some related studies including medical research, which were used as major data sources for my study.

3.1 System Dynamics Applications in the Public Health Area

The System Dynamics approach serves as a powerful tool to analyze chronic diseases since chronic diseases form part of a complex feedback and time varying (dynamic) systems. Chronic disease prevention is a dynamically complex problem in which interventions can have very different types of effects and will show impacts after different degrees of delay. The health care system is challenged to meet multiple goals, such as saving patients life in the emergency room and preventing disease in the first place, but these goals may conflict with each other due to limited resources. Many public health interventions fall short of their goal since they are made in a piecemeal fashion and with a lack of system-wide perspective. *Milstein et al.* in the paper “Background on System Dynamics Simulation Modeling with a Summary of Major Public Health Studies” described the basic concepts of system dynamics, general problems that System Dynamics simulation addresses and potential roles for System Dynamics modeling in the public health area [42]. The authors also listed many important System Dynamics studies that have been previously conducted in the public health area.

Homer et al. in the paper “System Dynamics Modeling for Public Health: Background and Opportunities” presented the power of the System Dynamics modeling approach in the

public health area and how a model helps public health agencies achieve their goals [43]. A System Dynamics simulation model incorporates diverse elements that have effects on the system environment and the interactions within the system, iteratively yielding possible outcomes. The authors built a simple model to illustrate the essential structure and policy inputs of chronic disease prevention. The simulation model projected different outcomes over 50 years for two different types of preventions (upstream and downstream) and the *status quo* scenario. By comparing the model output for three scenarios, public health policy makers could easily select the best one based on their goals and interest. The authors also outlined possible applications of System Dynamics modeling to more complicated problems in the public health area and other population health areas.

A System Dynamics model has been used to understand and evaluate a public health improvement program for chronic diseases by *Homer et al.* in the paper “Model for collaboration: how System Dynamics helped a community organize cost-effective care for chronic illness” [44]. Chronic diseases, such as diabetes and heart disease, impose a heavy burden in Whatcom County, Washington, due to aging of the population and growing prevalence of obesity. A large health care system improvement program called Pursuing Perfection (“P2”) would help to improve the care of chronic illness; but the adoption of the program introduces additional costs for the personnel, information system, screening and preventive education every year. The authors used a System Dynamics model to project system-wide costs from diabetes for *Status Quo* and full program adoption during a 20-year time period. The model also projected the program cost in the 20-year time period. By comparing the saving from community costs and additional costs from the program adoption, people could easily see a great deal of positive impact from the P2 program adoption. Another major contribution from this research is that the system costs including direct medical cost, employer loss and social loss were considered as burdens from diabetes (as Figure 3-1 shown). The separation would help to identify the benefit from the program adoption in different system sectors.

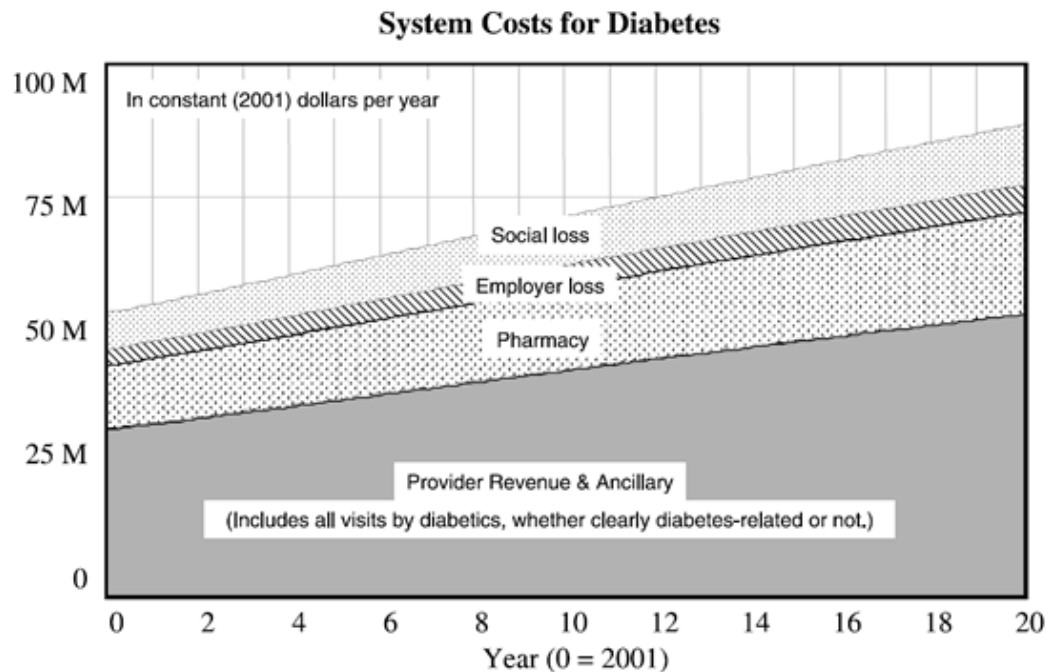


Figure 3-1. System Costs for Diabetes (taken from [44])

Tengs et al. developed a System Dynamics model to evaluate and compare different tobacco control policies [43]. The model divided the population into different age groups and gender groups. The simulations show that interventions yield different results when they are applied to different population groups. A given intervention could have more effective result on one population group than another one. For instance, preventing smoking initiation would have more effective results in young age groups than on elder age groups; on the other hand, encouraging cessation would have better result on older age groups than in younger age groups. The simulation results of health gains from preventing smoking initiation, encouraging cessation and avoiding relapse on different ages and genders were compared in terms of Quality-Adjusted Life-Years (QALYs). The measurement of QALYs quantitatively represents the gains from different health policies, both in terms of length and quality of life. Policy makers or policy analysts can judge the impression of these policies easily and pick the best one from the alternatives. It is often impossible to collect data for every parameter in the simulation model. A series of sensitivity tests were done in order to analyze the impact of assumptions in Tengs'

research. In the case of limited or no available data, reasonable assumptions are necessary. Sensitivity tests are able to analyze the impact of assumptions and help reduce the chance that they are exercising undue influence over the results.

Tengs et al. also applied System Dynamics model simulation to analyze the cost effectiveness of an anti-tobacco education program [41]. A System Dynamics model has been built to project costs and QALYs for status quo and intensive school based anti-tobacco education program over the next 50 years. The model evaluated anti-tobacco programs having different levels of intensity and duration. The results suggest that new costs introduced by the program cancel out saving from lower medical cost, but that total QALYs are increased by the program. Effectiveness of the program varies depending on degree and longevity of the program. Greater intensity and longer duration yields a lower cost for every additional QALY. In another word, the program is more efficient with greater intensity and longer duration.

Another tobacco control policy study from *Levy et al.* used a simulation model to provide justification for tobacco control to policy makers [45]. The model is employed to assess the effectiveness of current tobacco control policies. Long-term outcomes of current policies and future new policies can be projected from the simulation at a system level. The model also captures multiplicative effects when multiple tobacco control policies are applied synergistically. Multiple policies were evaluated in this study since different policies have effects in different demographic groups or smoking groups.

The System Dynamics modeling approach has been applied in public health strategic planning. *Lane et al.* employed a System Dynamics model to identify key factors that cause overly long waiting time at emergency rooms [46]. Early research pointed out that hospital bed shortage delays emergency room admission, causes cancellations of non-emergency admission and leads to more future emergency cases. The System Dynamics model simulated the scenarios that the hospital has more and less beds than current situation. The results do not show any change on the waiting time. On the other hand, demand for health services increase

the waiting time significantly. A snapshot view on a complex system could provide misleading information and cause dysfunctional policies.

Obesity is a well-known risk factor for type 2 diabetes. A good understanding on obesity and its treatment could help us to develop feasible interventions to slow down the prevalence of type 2 diabetes. The System Dynamics approach has been employed to analyze obesity as an epidemic in the public health area. *Homer et al.* developed a System Dynamics model to simulate prevalence of overweight and obesity, and to gain an understanding of obesity dynamics in U.S. population [47]. The model is calibrated to produce the best fit simulation result when compared to historical data. The calibration process found that growth in overweight and obesity prevalence decelerated during mid-to-late 90s and increasing prevalence in younger age groups would have a significant carryover effect on obesity in older age groups. Daily caloric imbalance relative to 1970 would need to be between 1% and 3% of the daily intake to explain the growth. The authors also used the model to experiment with several interventions. Experimental results conclude that a comprehensive intervention that targets all ages is more effective than an intervention only targeting school age children, but which has no linkage with the rest of community.

Obesity has also been analyzed at the individual level using the System Dynamics modeling approach. *Adbel-Hamid* demonstrated that the human body energy intake and consumption system using a System Dynamics model to simulate body weight change [48]. In terms of high level concepts, four inter-related subsystems: energy intake, energy expenditure, energy metabolism and body composition work together to create the dynamics of body weight. A System Dynamics model represented correlation and interactions among key factors in these four subsystems.

The model was also used to simulate weight changes in separated body components for different treatment. The two most common interventions (diet and exercise) were tested. Even though simulation results show both interventions could yield similar results in weight loss, exercise is more efficient in reduce fat mass in the body. Diet does not only lose fat mass, but

also loses significant amount of fat free mass (about 30% of total weight loss). In addition, the author tested different levels of exercise intensity. The simulation results turned out low intensity exercise is more effective on weight loss, but moderate and high intensity exercise is more effective on reducing percentage of body fat. Higher intensity exercise results yields an increase in fat free mass (mainly muscle) weight, which would reduce overall result on weight loss. The simulation results surprisingly suggest that high intensity exercise has a smaller loss on body weight when compared to moderate intensity exercise. One reason is that high intensity exercise results in a heavier fat free mass than the fat weight loss. The second reason is that human body selects different energy sources (such as glucose) for a faster energy transfer rather than draw energy from body fat response to higher level energy consumption in high intensity exercise.

Beside obesity, System Dynamics also has been widely applied to diabetes research. The U.S. Centers for Disease Control and Prevention (CDC) started a modeling project in 2003 to construct a system dynamic model of diabetes [49]. The project team used the diabetes model to gain a better understanding of the diabetes burden in the U.S. and to evaluate possible interventions. The model simulates the diabetes onset process using the population at risk and the diabetes progression. After the calibrating the model with historical data, the project team forecasted growth of diabetes and prediabetes prevalence through 2050 as the baseline for interventions evaluation.

With several different scenario experiments, the CDC model successfully demonstrated an ability to evaluate health intervention policies. Projected outcomes from upstream approach scenarios, downstream approach scenarios and balanced (combine both upstream and downstream) approach scenarios show that different intervention policies have different impacts. Downstream approaches are able to slow the growth of diabetes burden in a short time, but the benefit will be counteracted by the growth of diabetes prevalence. After the growth of diabetes onset slowed for a short period, it resumed rapidly. On the other hand, the result from the upstream intervention did not show any impact in the short run, but held back the prevalence of obesity, thus limiting diabetes onsets a great deal in the long run.

The CDC research focuses on the burden in the medical area. In scenario evaluations, the burden estimated from current policies and the burden after possible interventions were represented using the population of people with diabetes. The social, economic and human resource burden, however, were not included in this research. My research has the similar objective and same approach; hence, I adapted some model structure and use it as a starting point of my research. I also adapted some data for my research from data in the CDC model. I will describe the detailed adaptation process in chapter 4.

Jones et al. adopted the CDC research based on a similar System Dynamics model but with different scenario experiments [50]. The scenarios were characterized by the same categories (upstream, downstream and balanced approach) as scenarios in the CDC research; but they focus on social interventions rather than on the medical interventions using in the CDC model. For example, reducing obese prevalence was tested in Jones' research rather than reducing caloric intake. Like the CDC research, Jones' research used the size of the diabetic population to represent the burden.

Rees et al. at Synergia Limited developed a System Dynamics model to assist development of strategic diabetes policy for Manukau, a large multi-cultural city in New Zealand [51]. In the first stage of the work, the project team created a simple stock-and-flow model to depict disease progression. Figure 3-2 (taken from the project publication) illustrates concept of diabetes progression.

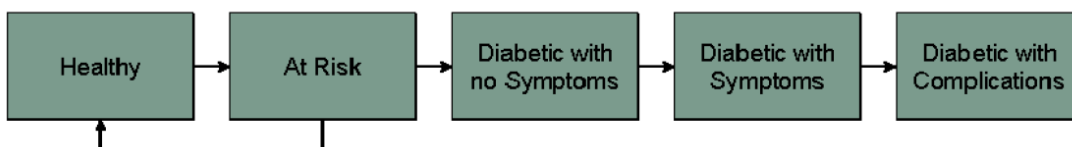


Figure 3-2. Concept of Diabetes Progress (taken from [51])

A more refined model was developed based on the CDC model to examine possible interventions and estimate required resources to implement them. The project team evaluated a range of interventions, and accounted for required resources from a whole-system perspective.

These interventions included an upstream approach, which works with the non-obese population, a downstream approach, which works directly with the diabetic population, and approach working with a potential high risk obese population. Similar to the CDC model, the New Zealand model classifies people into several racial groups and age groups since different racial groups and age groups have different risk of developing diabetes.

With a similar interest, I adapted a partial model structure from the New Zealand model since my research is also targeted on a multi-cultural urban health district. The adaptation process will be described in chapter 4.

3.2 Major Data Sources

Data collection is a crucial step in model development before model parameterization. Modelers use simulation models to recreate real life problems in a controlled virtual environment by using mathematical equations. All factors in the real world must be quantitatively converted into mathematical equations and numeric values in the model parameterization step. The question is to identify the right quantity for each factor. In order to answer this question, modelers need collect data for these factors. For my research I mainly collect data from sources that can be grouped into three categories: local health authority reports, statistical surveys and the Canadian Census, and research papers.

3.2.1 Local Health Authority Reports

The Saskatoon Health Region Authority releases a report every year summarizing health region operations in the previous year [8, 33, 52, 53]. These annual reports supply information about the work force, facilities, operation cost, and service provided in the health region. Annual reports also describe demographic information and its dynamics about the health region. I was able to collect detailed demographic information especially regarding residents with Registered Indian status, who are at particularly high risk with respect to diabetes [69]. Annual reports describe the health status of residents in the region by using important health indicators; prevalence of diabetes is one of health indicators in the reports. I was able to find the diabetes prevalence in the health region directly from the reports. Besides the annual reports, the

Saskatoon Health Region Authority released a detailed health status report every five years [54]. This report listed some key indicators, including population size, structure, birth rate, death rate and more, as attributes of overall health status of SHR population. The values of many parameters in my model were drawn from in this report. Both annual reports and health status reports can be obtained at the SHR website.

"Diabetes 2000" is a strategic recommendation for diabetes published by Saskatchewan Health in year 2000 [55]. This document describes diabetes status – including prevalence and incidence rates – in Saskatchewan in 1996. These rates are characterized by age, gender and race, and could be perfectly plugged into my model. "Epidemiological Account of Diabetes in Saskatchewan: Diabetes Prevalence Rates in Health Districts, 1996" is another diabetes report released by Saskatchewan Health [56]. This report listed age and sex, and characterized prevalence of diabetes in all health districts. The data can be used in the calibration step.

The Health Quality Council recognizes the growing burden in Saskatchewan due to diabetes and possible improvement in disease management in the report "Quality of Diabetes Management in Saskatchewan" [34]. The supplementary tables and figures for this report provide a significant amount of data about diabetes in Saskatchewan in the 2003-04 fiscal year. These data including age-sex specific prevalence, age-sex specific incidence, incidence of end stage renal disease and mortality rates that can be adopted to my research.

3.2.2 Statistical Surveys and the Canadian Census

Statistical surveys are powerful instruments for collecting quantitative information in a population. They obtain first-hand raw information directly from targeted population. For my research I obtained data from several statistical surveys collected by Statistics Canada and other agencies.

The National Population Health Survey (NPHS) is a broad health survey about Canadians' physical and mental health conducted by Statistics Canada. The NPHS collects cross-sectional and longitudinal data on economic, social, demographic, occupational and environmental health related data [57]. I have obtained the number of diabetes cases in Saskatchewan in the sample

set from the NPHS Cycle 3 Public Use Microdata File and use that to calculate diabetes prevalence in Saskatchewan. Meanwhile, I obtained the body mass index information of Saskatchewan residents in the sample set, and estimated overweight and obesity prevalence in Saskatchewan.

The Canadian Community Health Survey (CCHS) is another important cross-sectional health related survey from the Statistic Canada. I collected a considerable amount of data from the CCHS for my model. First, the CCHS asks health utility index (HUI) attributes in the questionnaires. Hence, I was able to collect HUI data for normal weight, overweight/obese and diabetic population that measured in the unit of HUI, version 3 from CCHS Cycle 1.1 public use microdata file. These HUI data initialize the HUI component in my model, which qualitatively measures improvement in health-related quality of length that result from interventions. Furthermore, I collected BMI data for population younger than 20 years from the CCHS. The obesity measurement for children and youth is different from measurement for adults. The CCHS Cycle 2.2 questionnaires cover measured weight and height data which can be used to measure obesity status for children and youth.

Statistics Canada conducts a census every five years to capture a detailed demographic picture about the Canadian population. I found data on the particular population structure of the SHR from 2001 Census data, and the finding has been calibrated with data from other sources to determine the initial population for my study.

3.2.3 Related Research

In previous section, I introduced some pioneering research of the System Dynamics approach in public health area. Two of these studies were specifically for diabetes and intervention: the CDC model and the New Zealand model. Although these two models targeted on different geographic area and populations but maintained many similar structure, I was able to use some common data for the initial values of parameters in my model.

3.3 Summary

In this chapter, I reviewed some pioneering studies of applications of the System Dynamics methodology, which give an advanced starting point for my study. These studies adopt the System Dynamics modeling approach to analysis and understand issues in chronic disease management. Some of them have a broad scope, such as tobacco control; some of them focus on individuals, such as weight control; but all of these studies were creating a system-wide view for their targets and tried to estimate the impact over entire system rather than a small immediate sector from interventions.

Beside the related research, I briefly described major data sources used in my research. Some statistical data from surveys, the Canadian Census and local health authority reports can be directly plugged into the model, but some requires tuning and adjustment. I will describe the detailed data tuning process in the next chapter.

CHAPTER 4

SIMULATION MODEL FOR DIABETES IN SASKATOON HEALTH REGION

In this chapter, the development of my model is described. First, I converted the New Zealand and the CDC diabetes models' structures to Vensim, the software selected to build my model. During the adaptation, I modified the original structure to represent the local population structure and health care system. The model was also modified to accommodate our prospective goals. Secondly, I extended the model with additional interrelated areas such as Health Related Quality of Life. These additional sections would help users to observe and compare the impact of different policies on different components of the situation.

This chapter also presents the detailed model structure. The model contains two core sections and several accessory sections. The two core sections are the normoglycemic population section and the hyperglycemic population section. These two sections provide the basic population structure of the model and the formulae governing the dynamics within and between normoglycemic population and hyperglycemic population used in the simulation. The accessory sections are the structure associated with the initial population, HRQoL, mortality, prediabetes diagnosis, diabetes diagnosis and early stage complication diagnosis. Beside these accessory sections, the model has a calibration section, which will be described in the calibration chapter. The model also has several customized output sections to help a user gain a better understanding of simulation results.

4.1 Development of the System Dynamics Model

4.1.1 Adaption of the New Zealand Model and the CDC Model

In the last chapter, I reviewed several research publications about the diabetes model from the U.S. Centers for Disease Control and Prevention. These contributions provide a solid foundation for my study. With a similar research objective, I adapted the diabetes onset and progress structure from the CDC model illustrated in Figure 4-1. In the CDC model, the

hyperglycemic population is classified into three levels according to hyperglycemia progress: prediabetes, diabetes without complication, and diabetes with complication; and two stages according to hyperglycemia diagnosis status: diagnosed hyperglycemia and undiagnosed hyperglycemia. During the adaptation, I applied a similar classification. The hyperglycemic population in my (SHR) model is classified into four levels according to hyperglycemia progress: prediabetes, diabetes without complication, diabetes with early stage macrovascular complication and diabetes with late stage macrovascular complication. With the exception of people with late stage macrovascular complication, the hyperglycemic population in the SHR model is classified into the same two categories as in the CDC model by hyperglycemia diagnosis: diagnosed hyperglycemia and undiagnosed hyperglycemia. This classification clearly separates the hyperglycemic population into seven different stocks, so I can easily track changes in overall diabetes progression.

The New Zealand model separates the normoglycemic population – called the “general population” – according to age and obesity status as shown in Figure 4-2. This grouping method separates the normoglycemic population based on their latent risk of developing Type 2 diabetes since Type 2 diabetes is highly relevant to aging and obesity. By adapting this grouping method in my model, the model simulates Type 2 diabetes’ onset and progression in details. Moreover, model users can have a detailed observation and better understanding of the potential risk of developing Type 2 diabetes.

Both the CDC model and the New Zealand Model seek to simulate diabetes prevalence. By adapting similar structures from these pioneer studies, I seek to draw on insights from researchers involved in building those models, and to avoid mistakenly creating an unreasonable model.

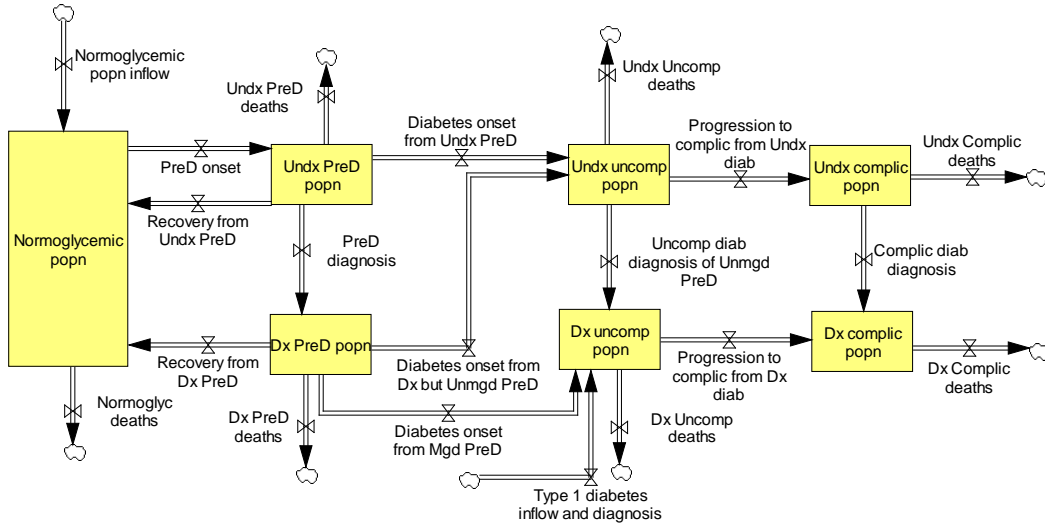


Figure 4-1. Diabetes Onset and Progress Structure in the CDC Model

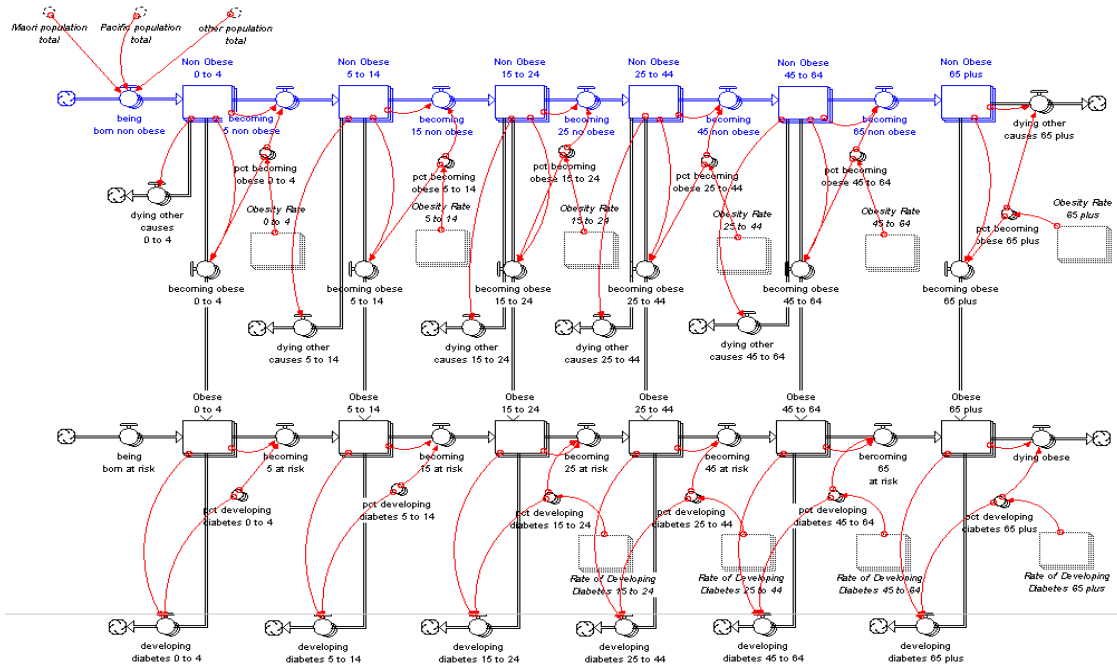


Figure 4-2. General Population Structure in the New Zealand Model

4.1.2 Structure Modification and Correction

Although the New Zealand model helped me starting my modeling process, during the adaptation process, I found that some components in this model do not fit my research or the

specifics of the local situation. Therefore, I selectively adapted and modified the model.

The New Zealand model presents the process of aging and the process of becoming obese admirably. It logically shows the population flows from the normal weight to an obese state and then to diabetes. However, the version of the model examined seems to be incomplete; there is no death outflow from the obese population, but the New Zealand model has an outflow “dying other causes” for every non-obese population stock. Nevertheless, there is no outflow for obese population stocks except from the 65plus stock. The absence of death flows leads an obvious issue: it does not reflect the situation of the real world, where deaths happen for every age. If the obesity rate is high in a community, then obviously the overall health status will be getting worse since with more people become obese; the overall death rate will increase as many chronic diseases are highly associated with obesity. However, the simulation results for the model available to us show a decreasing overall death rate because no obese people will die until they reach age 65. As a solution for our model, I added death outflows that are similar to those of non-obese general population stocks for each obese population stock.

Although obese population has the highest level of risk of developing Type 2 diabetes, normal weight and overweight population also have levels of risk of developing Type 2 diabetes. The New Zealand model does not have a flow representing developing diabetes from normal weight population, and the only path to develop diabetes is becoming obese first. Hence, I added developing diabetes from normal weight and overweight population flow into my model.

Both the CDC model and the New Zealand model lack detailed age structures in the diabetes progression section. The CDC model does not separate the population by age but instead use a coefficient to adjust the risk of developing diabetes for proportion in the population group. The structure does not capture the co-variance between ethnicity and age structure of the population in the SHR: the Caucasian population tends to be older, but the Aboriginal population tends to be younger. Most notable, the model does not track population age change over the simulation period, which could be several decades. The New Zealand model separates non-diabetic population into 6 age groups, but there are no similar age groups for the

diabetic population. Without age group structure for the hyperglycemic population, I found the model may produce misleading results when population flows from the normoglycemic population section into the hyperglycemic population section. When acquiring diabetes, all individuals originating from different normoglycemic population age groups are aggregated together since there is no age structure in the hyperglycemic population section. For the younger age groups, the expected life span in those age groups is longer than the expected life span for the aggregated diabetics. The model is thus capable of showing that acquiring diabetes will reduce the life span! For the older age group, however, the lack of age structure in the diabetic section causes signification artifacts in the results. For example, the expected life span for the 65plus age normoglycemic group is 10 years, but the expected life span for aggregated diabetics is more than 10 years in the model. That means for the 65plus age group, acquiring diabetes will not reduce the life span but instead increases the life span. In order to avoid this artifact, I extended the age structure into the hyperglycemic population section. My model has the age group structure – 17 5-years age categories, starting from age 0 and ending at age 80 plus – for both normoglycemic population and hyperglycemic population.

The CDC model and the New Zealand model were built to analyze research questions related to the diabetes burden in U.S. and New Zealand. The structure I adopted from these models above does not capture some unique characteristics of diabetes prevalence in SHR. Therefore, I further modified the adapted structure in order to represent the local situation.

First, I separated the normal weight, overweight and obese population. Both overweight and obese populations suffer a higher risk of developing Type 2 diabetes and other chronic conditions than do the normal weight population. Statistics Canada reports that the odds ratio of developing diabetes for the overweight and obese population are 1.73 and 3.79 (where the acceptable weight population is the control group) [58]. This grouping is able to highlight the different risks of developing diabetes between different populations.

Second, I changed the ethnic classification of groups in my model based on Saskatoon local ethnic classification. Both the CDC model and the New Zealand model classified the

population into different ethnic groups. In the CDC model, the black and Hispanic subpopulation were separated from others since these two ethnic groups have a higher risk of developing Type 2 diabetes. In the New Zealand model, Maori and Pacific Islanders were analyzed separately based on the similar considerations. In Chapter 2, I noted that in the SHR diabetes has higher prevalence among Aboriginal subpopulation (especially among Aboriginal women) in the SHR. Hence, I classified the population into two ethnic groups in my model: Aboriginal and other. This classification allows us compare dynamics of both ethnic groups, and allows us to investigate the causes contributing to the higher prevalence among Aboriginal people.

Beside the local ethnic group structure, I added a gender group structure into the model. The gender group structure assists the ethnic group structure to finely classify the population based on different risk of developing Type 2 diabetes and accurately characterize the local diabetes situation. The gender group structure would also help us to extend the model to gestational diabetes in future. These changes greatly increase accuracy of the model, but unfortunate also the complexity.

4.2 Model Structure

With these corrections and modifications, my model is able to systemically represent the high-level elements contributing to the burden from Type 2 diabetes in the SHR. For a complete simulation I still need equations, parameters and initial values for the model. In this section, I describe the model structures and equations.

The model contains two core components: the normoglycemic population and the hyperglycemic population. The normoglycemic population section represents people in the SHR whose blood glucose levels lie within a normal range. This population group is divided into three major subgroups by weight categories: normal weight, overweight and obese. The model simulates people's weight change by a flow of the population among weight subgroups. The weight subgroups are represented as stock variables in the model sketch. Within a subgroup, the population is classified into smaller scale subgroups by age, ethnicity and gender.

These final classifications are represented using subscripts in equations in order to keep the model sketch clean and organized.

The hyperglycemic population section represents people who already developed prediabetes or Type 2 diabetes in the SHR. The hyperglycemic population section is first divided into four hyperglycemia progress stages: prediabetes, diabetes without complication, diabetes with early stage macrovascular complication and diabetes with late stage macrovascular complication. Every hyperglycemia progress stage includes two hyperglycemia diagnosis statuses: undiagnosed and diagnosed, except the diabetes with late stage macrovascular complication, which are considered to be all diagnosed according to our definition. Hence, the hyperglycemic population is divided into seven major subgroups by hyperglycemia progress stages and hyperglycemia diagnosis status in the model. The population in each major subgroup is further divided by age, ethnicity and gender as subscripts in equations.

Beside the two core sections, the model has a Health Related Quality of Life (HRQoL) section. The HRQoL section calculates aggregated HRQoL-related measures for population in different groups. In other words, this section quantitatively converts aggregated quality of life associated with an individual's health status from an abstract concept to a numerical value. Based on the HRQoL for different population categories (which are assumed to be identical across ethnic groups), this section of the model calculates the accumulated Quality Adjusted Life Years lived by the population as a whole. By comparing the results simulated for a baseline *status quo* scenario and a different scenario simulating an intervention, users can gain insights into the potential impact of an intervention. Although the comparison of HRQoL is not applied in my study, the HRQoL section can serve as a useful tool for future work.

One purpose of the model is examining interventions. Most interventions are reflected by rate changes in the model. For instance, if we want to simulate the introduction of a physical activity program for high school students, the direct manner to present this intervention in the model is by decreasing the *becoming overweight* and the *becoming obese* flows for school age population groups. I created an easy-to-use control interface for key rates in the model; hence,

users could easily introduce new intervention into the system.

4.2.1 Normoglycemic Population Section

The normoglycemic population is the population in the SHR except for the prediabetic and diabetic population. The normoglycemic population is the population group who could potentially develop Type 2 diabetes. Dependent on age, ethnicity, gender and level of obesity, people in the normoglycemic population section have different levels of risk of developing Type 2 diabetes. It is essential to recognize the different risk of developing diabetes between people; hence, I separate normoglycemic population into different subgroups. First, I classify people into three groups by their body mass index: normal weight population, overweight population and obese population. In accordance with the standard classification [59], people who have a BMI less than 25 are classified into the normal weight population group; people who have BMI greater than or equal to 25 but less than 30 are classified into the overweight population group; and people who have BMI greater than or equal to 30 are classified into the obese population group. It is a well-known fact that Type 2 diabetes is highly associated with obesity. People who are overweight or obese have much higher risk of developing Type 2 diabetes than normal weight people. The standard classification can highlight the higher risk among overweight and obese population in a simulation and capture impacts from interventions that cause changes in the weight distribution of the population.

Beside body mass index, age is another important factor which makes a great contribution to the risk of developing Type 2 diabetes. The National Diabetes Surveillance System (NDSS) data shows that Type 2 diabetes prevalence and incidence are much higher among the elderly population compared to the young population (see Figure 4-3). In order to show this difference, I further divide the population in each weight group into 17 different age groups, using commonly used 5-year age categories: 0 to 4, 5 to 9, 10 to 14, 15 to 19, 20 to 24, 25 to 29, 30 to 34, 35 to 39, 40 to 44, 45 to 49, 50 to 54, 55 to 59, 60 to 64, 65 to 69, 70 to 74, 75 to 79 and 80 plus.

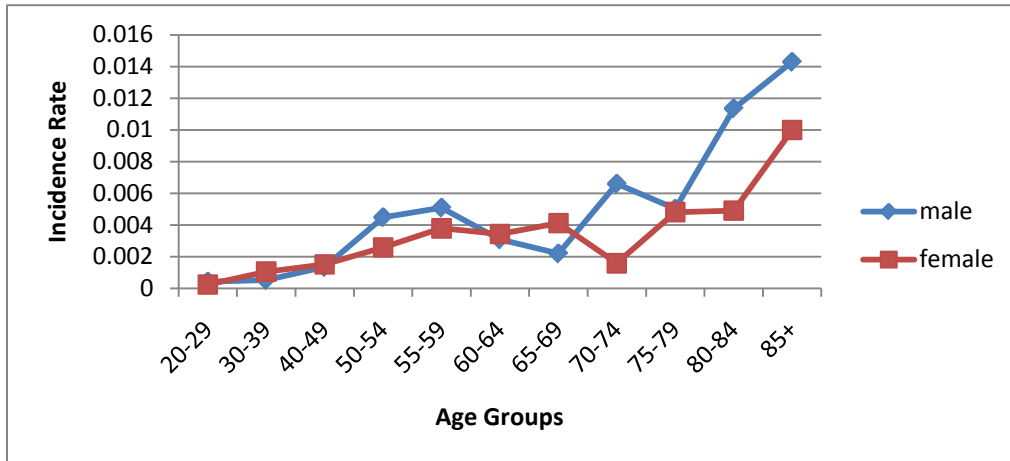


Figure 4-3. Incidence Rate of Type 2 Diabetes in Saskatchewan, estimated from NDSS

Figure 4-4 illustrates the conceptual structure of the normoglycemic population section in my model. In the actual model sketch, all age groups are represented by subscripts in the equations rather than the individual stocks included in Figure 4-4. I can easily add new parameters and modify equations that apply to all subgroups in the normoglycemic population section by using subscripts, but because subscripts hide many aspect of model structure, it is difficult to visually illustrate the aging chain in the model using subscripts. Hence, I redrew age groups to stocks for an easy visual understanding of the aging chain structure. The normoglycemic population stocks are grouped into three segments: normal weight population, overweight population and obese population. Three aging chains for these three segments are circled by different color in Figure 4-4. There are total 17 age group stocks for each aging chain. Because 17 stocks and flows between stocks are too much to draw, I did not draw all 17 stocks in Figure 4-4 but selected 5: the first age group, the last age group and three groups between the first age group and the last age group to show the chain structure.

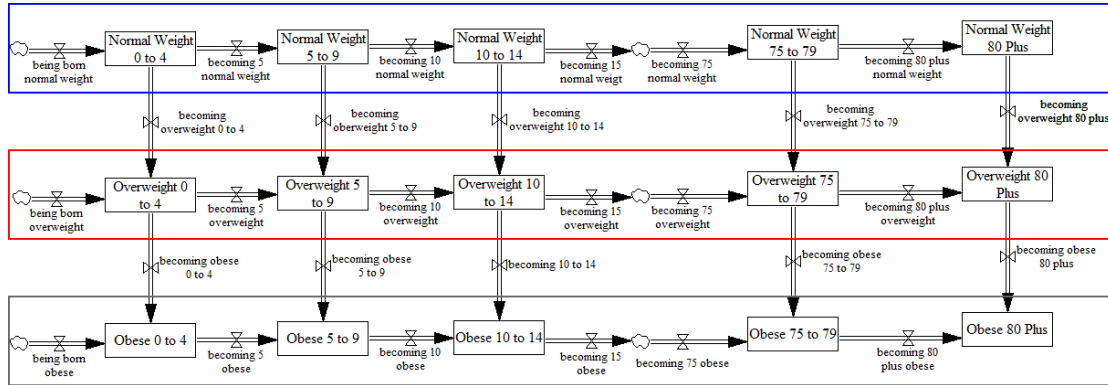


Figure 4-4. Normoglycemic Population Aging Chain Structure

The top portion of Figure 4-4 circled by the blue box is the aging chain structure for the normal weight population. An aging flow connects every two adjacent age group stocks and forms chain structure. These aging flows move people from younger population stocks to older population stocks as people age. An aging flow is an outgoing flow, speaking from the view point of the younger age group stock but it is also an incoming flow from the view point of the older age group stock. Hence, every age group stock except the *0 to 4* and the *80 plus* age group has two aging flows; one from the previous age group and one to the next age group. Figure 4-5 shows a generic normal weight population stock and all flows that connect with the stock. The incoming aging flow is named “*normal weight aging from previous age group*” and the outgoing aging flow is named “*normal weight aging to next age group*” in Figure 4-5.

In order to simplify the calculation of the aging flow rates, I made the assumption that the population within each age group is evenly distributed across the ages included within that group. Hence, rates of the age flows (as measured in number of people per unit time) are only influenced by the width of the interval and population of the younger age group. For example, on average 20% (1/5) of the population in the *normal weight age group 5 to 9* age group ages to the *normal weight age group 10 to 14* age group every year.

The first age group – *normal weight 0 to 4* – does not have an incoming aging flow since it has no age group younger than it. However, it has a unique incoming flow from outside of the system: *being born normal weight*. Every year the system generates a certain amount of

newborn infants based on total population in the system and the birth rate. Theoretically, only a fraction of newborn infants flow to the normal weight population section and other infants flow to the overweight or obese population section according to their birth weight. However, the birth weight has a U-shape relationship with risk of developing Type 2 diabetes at later age [60]. I assumed all infants are born into the normal weight category in order to simplify the model by setting the fraction of normal weight infant in all newborn infants to 1. The fraction of normal weight infant can be set to an accurate value later when data is available.

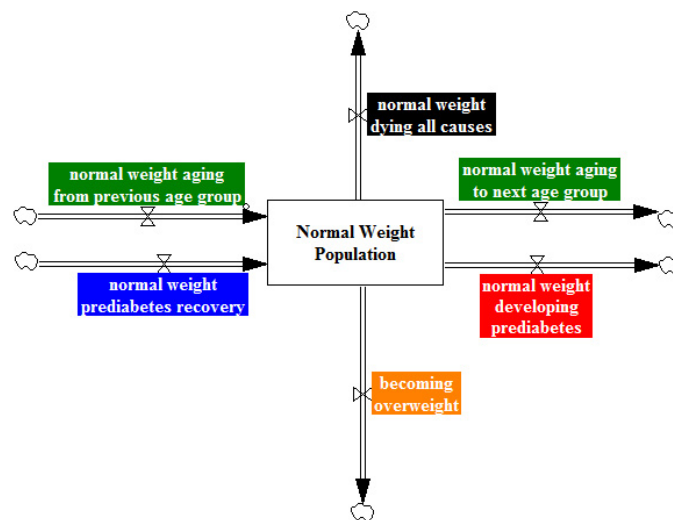


Figure 4-5. Normal Weight Population Stock and Flows

The *normal weight 80 plus* is the last stock in the normal weight population aging chain. Hence, unlike other stocks in the aging chain, it has no outgoing aging flow towards the next age group stock. The population stays in the stock until they die or their health status changes.

A part of the population in each normal weight population stock is dying from many causes, such as illness, accidents or other conditions other than diabetes. This part of population flows out of the system through the *normal weight dying all causes* flow. The flow rate is dependent on the mortality risk of the group. Hence, the rates vary across the population stocks since different age groups have different mortality rates. The mortality rate for each age and gender group in normal weight normoglycemic population is calculated by the number of

deaths in Saskatchewan and total population in Saskatchewan in 2001. An identical mortality rate is applied to both ethnic groups.

All normoglycemic subpopulations have a risk of developing hyperglycemia; young age groups have lower risks, elderly age groups have higher risks. Reflecting this, a developing prediabetes flow is associated with all normal weight population stocks. The developing prediabetes flow for a normal weight age group is controlled by *prediabetes incidence base rate normal weight*, *prediabetes onset risk age multiplier*, *prediabetes onset age coefficient* and the size of population in the age group. The *prediabetes incidence base rate normal weight* and the *prediabetes onset multiplier* are obtained from the CDC model directly. The *prediabetes onset risk multiplier* is the coefficient that highlights the different risk of developing diabetes from different age group. However, this coefficient is too broad since it only differentiates the risks of developing diabetes in young population and in elderly population. I introduced a new coefficient, the *prediabetes onset age coefficient*, to differentiate the different risks of developing diabetes among child, adolescent and adult subpopulation groups. The *prediabetes onset age coefficient* is set to 0.1 before age 20 and 1 after age 20. Results from multiplication of *prediabetes incidence base rate normal weight*, *prediabetes onset age multiplier* and *prediabetes onset age coefficient* highlight different risk of developing hyperglycemia with different age groups.

The normal weight population is defined as people with BMI less than 25. When people gain weight and the BMI exceeds 25, they are no longer classified as being of normal weight. They move to the next weight category, the overweight population, through the *becoming overweight* flows. Rates of the *becoming overweight* flows are calculated based on the population in each normal weight stock and the incidence of becoming overweight for the stock. The incidence of becoming overweight is controlled by *incidence of overweight base rate*, *weight change age coefficient*, *weight change gender coefficient* and *weight change ethnic coefficient*. An appraised value is assigned to the *incidence of overweight base rate* to initialize the model. A more accurate value of incidence of becoming overweight is applied by

calibrating these three weight change coefficients.

Equation 4.1 below shows the equation for the normal weight age population stocks except for those associated with the first and the last age group. Equation 4.2 is for the 0 to 4 age group and Equation 4.3 is for the 80 plus age group. They are slightly different from Equation 4.1 since both age groups only have one aging flow. All age groups in these equations contain subscripts for ethnic groups and gender groups in the model, but I did not list them here.

$$\begin{aligned}
 & \textit{normal weight population}[\textit{middle age groups}](T) \\
 &= \int_0^T [\textit{normal weight population aging} [\textit{previous age groups}] \\
 &\quad - \textit{normal weight population aging}[\textit{middle age groups}] \\
 &\quad - \textit{normal weight dying all causes}[\textit{middle age groups}] \\
 &\quad - \textit{becoming overweight}[\textit{middle age groups}] \\
 &\quad - \textit{developing prediabetes from normal weight}[\textit{middle age groups}] \\
 &\quad + \textit{prediabetes recovery normal weight}[\textit{middle age groups}]]dt.
 \end{aligned}
 \tag{4.1}$$

$$\begin{aligned}
 & \textit{normal weight population}[0 \text{ to } 4](T) \\
 &= \int_0^T [\textit{being born normal weight} - \textit{normal weight dying all causes}[0 \text{ to } 4] \\
 &\quad - \textit{becoming overweight}[0 \text{ to } 4] - \textit{normal weight population aging}[0 \text{ to } 4] \\
 &\quad - \textit{developing prediabetes from normal weight}[0 \text{ to } 4] \\
 &\quad + \textit{normal weight prediabetes recovery}[0 \text{ to } 4]]dt.
 \end{aligned}
 \tag{4.2}$$

$$\begin{aligned}
& \text{normal weight population}[80 \text{ plus}](T) \\
&= \int_0^T [\text{normal weight population aging [75 to 79]} \\
&\quad - \text{normal weight dying all causes}[80 \text{ plus}] \\
&\quad - \text{becoming overweight}[80 \text{ plus}] \\
&\quad - \text{developing prediabetes from normal weight}[80 \text{ plus}] \\
&\quad + \text{normal weight prediabetes recovery}[80 \text{ plus}]]dt.
\end{aligned}
\tag{4.3}$$

The initial value of the normal weight population stocks are calculated based on the total normoglycemic population in the SHR and the overweight/obese rate for the Saskatchewan population.

The middle portion of Figure 4-4 that is circled by a red box is the aging chain for the overweight population. The overweight population aging chain has the same number of stocks as the normal weight population aging chain. All age groups are associated with 5 year age category up to age 80. The population moves to the corresponding age group stock in the overweight segment from the normal weight segment when their BMI changes to exceed 25. Figure 4-6 illustrates an overweight population stock and associated flows. The structure of an overweight population stock is very similar to that of a normal weight population stock. Every overweight population stock has two aging flows except the age group *0 to 4* and the age group *80 plus*. Beside aging flows, an overweight population stock also has a dying all causes flow, a developing prediabetes flow and a prediabetes recovery flow.

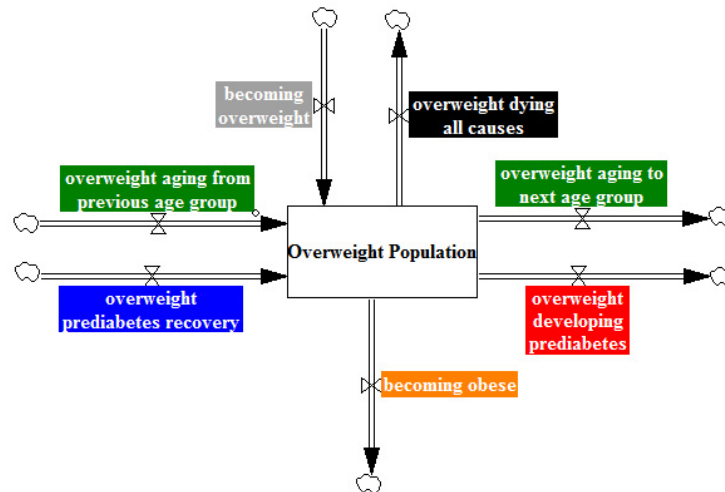


Figure 4-6. Overweight Population Stock and Flows

A *becoming overweight* flow connects a *normal weight general population* stock and an *overweight general population* stock in the same age group. As I explained before, the rate of a *becoming overweight* flow is controlled by incidence of overweight. In reality, a small portion of overweight people could lose weight and become normal weight again. I made the assumption that incidence of overweight is a net value, which includes people become overweight and people back to normal weight, to simplify the model. This assumption allows the model to examine the scenario where the incidence of becoming overweight changes to a smaller value, but does not allow the model to examine the scenario where people flow back to the *normal weight general population* stock from the *overweight general population* stock without necessary modification.

The criterion for a person to be considered overweight is BMI higher than 25 but lower than 30. When a person's BMI exceeds 30, they move to the next level, to the obese population segment through a *becoming obese* flow that is colored in orange in Figure 4-6. Structurally identical to *becoming overweight* flow, the rate of *becoming obese* flow is controlled by the incidence of obesity and population in the overweight population group. The incidence of obesity is the product of *incidence of obesity base rate*, *weight change age coefficient*, *weight change gender coefficient*, and *weight change ethnic coefficient*. Absent a reliable data source

on the weight change dynamics over time, these coefficients are adjusted by a calibration process.

The *Overweight dying all causes* flow, *overweight prediabetes recovery* flow and *developing prediabetes from overweight* flow are structurally identical to the corresponding flows in the normal weight segment. However, the flow rates show a significant difference since the two population groups have different level of risks of death and developing prediabetes. Mortality of the overweight population is calculated based on mortality of normal weight population and relative risk of death for different BMI levels. The rate of *developing prediabetes from overweight* flow is calculated based on *prediabetes incidence rate for normal weight population* and *prediabetes onset overweight multiplier*. While the CDC model did not disaggregate the population by weight status, it does make some attempts to capture the impact of overweight and the *prediabetes onset overweight multiplier* is set to 1.7 according to the CDC model. The prediabetes recovery rate for overweight population initially is set to 10% per year according to the CDC model. This value seems to be too high for the SHR; hence, it is changed to 3% instead.

Equations 4.4 to 4.6 explain mathematically how these flows work together to create dynamics of an overweight population age groups. Similar to the normal weight population groups, age group *0 to 4* has a unique incoming flow *being born overweight* and age group *80 plus* has no outgoing aging flow.

overweight population[middle age groups] (T)

$$\begin{aligned} &= \int_0^T [\textit{overweight population aging [previous age groups]} \\ &\quad - \textit{overweight population aging[middle age groups]} \\ &\quad - \textit{overweight dying all causes[middle age groups]} \\ &\quad - \textit{becoming obese[middle age groups]} \\ &\quad + \textit{becoming overweight[middle age groups]} \\ &\quad - \textit{developing prediabetes from overweight[middle age groups]} \\ &\quad + \textit{prediabetes recovery overweight[middle age groups]}]dt. \end{aligned}$$

(4.4)

overweight population[0 to 4] (T)

$$\begin{aligned} &= \int_0^T [\textit{being born overweight} - \textit{overweight population aging[0 to 4]} \\ &\quad - \textit{overweight dying all causes[0 to 4]} - \textit{becoming obese[0 to 4]} \\ &\quad + \textit{becoming overweight[0 to 4]} \\ &\quad - \textit{developing prediabetes from overweight[0 to 4]} \\ &\quad + \textit{prediabetes recovery overweight[0 to 4]}]dt. \end{aligned}$$

(4.5)

$$\begin{aligned}
& \textit{overweight population}[80 \textit{ plus}] (T) \\
&= \int_0^T [\textit{overweight population aging [75 to 79]} \\
&\quad - \textit{overweight dying all causes}[80 \textit{ plus}] - \textit{becoming obese}[80 \textit{ plus}] \\
&\quad + \textit{becoming overweight}[80 \textit{ plus}] \\
&\quad - \textit{developing prediabetes from overweight}[80 \textit{ plus}] \\
&\quad + \textit{prediabetes recovery overweight}[80 \textit{ plus}]]dt.
\end{aligned}
\tag{4.6}$$

In a manner similar to what is used for the normal weight population, the initial value of the overweight population stocks is obtained from the total normoglycemic population in the SHR and overweight/obese rate for Saskatchewan population.

The last segment in the normoglycemic population section is the obese population segment. This segment is circled by a grey box in Figure 4-4. People in this segment have BMI higher than 30. Just as in the two previous segments, this segment has 17 age groups and each age group is further divided into subpopulations according to ethnicity and gender. The model structure and equation structure are very similar to the structures in the overweight population segment. The only difference in structure is that an obese population stock does not have a progress flow towards to the next heavier normoglycemic population segment since the obese population segment is the last segment in the normoglycemic population section. Figure 4-7 below shows the structure of an obese population stock and associated flows. Equations 4.7 to 4.9 mathematically characterize the formulation of the obese population stocks and flows.

obese population[middle age groups](T)

$$\begin{aligned}
 &= \int_0^T [\textit{obese population aging [previous age groups]} \\
 &\quad - \textit{obese population aging[middle age groups]} \\
 &\quad - \textit{obese dying all causes[middle age groups]} \\
 &\quad + \textit{becoming obese[middle age groups]} \\
 &\quad - \textit{developing prediabetes from obese[middle age groups]} \\
 &\quad + \textit{prediabetes recovery obese[middle age groups]}] dt.
 \end{aligned}$$

(4.7)

obese population[0 to 4](T)

$$\begin{aligned}
 &= \int_0^T [\textit{being born obese} - \textit{obese population aging[0 to 4]} \\
 &\quad - \textit{obese dying all causes[0 to 4]} + \textit{becoming obese[0 to 4]} \\
 &\quad - \textit{developing prediabetes from obese[0 to 4]} \\
 &\quad + \textit{prediabetes recovery obese[0 to 4]}] dt.
 \end{aligned}$$

(4.8)

obese population[80 plus](T)

$$\begin{aligned}
 &= \int_0^T [\textit{obese population aging [75 to 79]} \\
 &\quad - \textit{obese dying all causes[80 plus]} + \textit{becoming obese[80 plus]} \\
 &\quad - \textit{developing prediabetes from obese[80 plus]} \\
 &\quad + \textit{prediabetes recovery obese[80 plus]}] dt.
 \end{aligned}$$

(4.9)

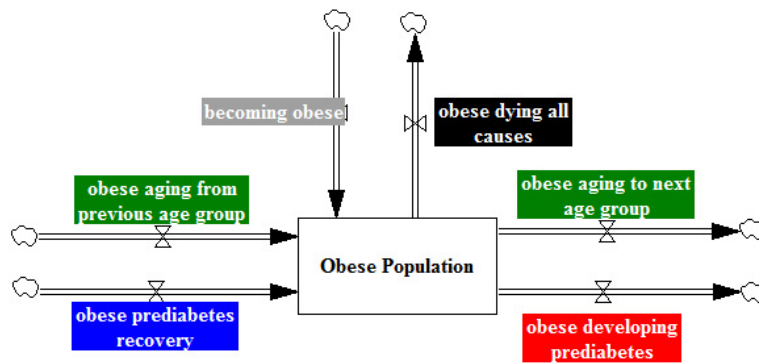


Figure 4-7. Obese Population Stock and Flows

The initial value of the obese normoglycemic population, like the initial value of the normal weight and overweight normoglycemic population, is calculated by the total normoglycemic population in the SHR and Saskatchewan overweight/obese rate. The mortality of the obese populations is calculated based on the mortality of the normal weight population and relative rate of death. The rate of the *becoming obese* flow is controlled by incidence of obesity base rate and three weight change coefficients. Again, the values of the three weight change coefficients are adjusted by calibration due to lack of reliable data. The rate of *developing prediabetes from obese* flow is based on *prediabetes incidence base rate obese* and the size of the obese population in the stock. The *prediabetes incidence base rate* is calculated using the rate of *prediabetes incidence base rate normal weight* multiplied by *prediabetes onset obese multiplier*. *Prediabetes onset obese multiplier* is set to a constant value of 2.6, which has been used in the CDC model. The rate of the *prediabetes recovery obese* flow is set to 0 due to the assumption that “obese people must lose weight and become overweight before they can recover from prediabetes”.

4.2.2 Hyperglycemic Population Section

One of the major objectives of this study is to simulate the dynamics of the diabetic population in the SHR. The “hyperglycemic population” section is intended to simulate the dynamics in the hyperglycemic population and between the hyperglycemic and the

normoglycemic population. The section provides information regarding prevalence of Type 2 diabetes by monitoring the population in the hyperglycemic population stocks, and information regarding incidence rate of Type 2 diabetes by monitoring the rates of flows. The section also provides a testbed for downstream interventions. By changing rates of various flows from the *status quo* or adding exogenous conditions to the section “hyperglycemic population”, the model can simulate different possible downstream interventions and project outcomes from the interventions.

The population in the section “hyperglycemic population” is classified into different population stocks based on several criteria: diagnosis of the disease, progression of the disease and age, gender and ethnicity. The classification distinguishes the unique characters of each population stock. These population stocks are connected by flows and these flows capture the dynamics in the hyperglycemic population. Figure 4-8 is the simplified model structure of the section “hyperglycemic population”.

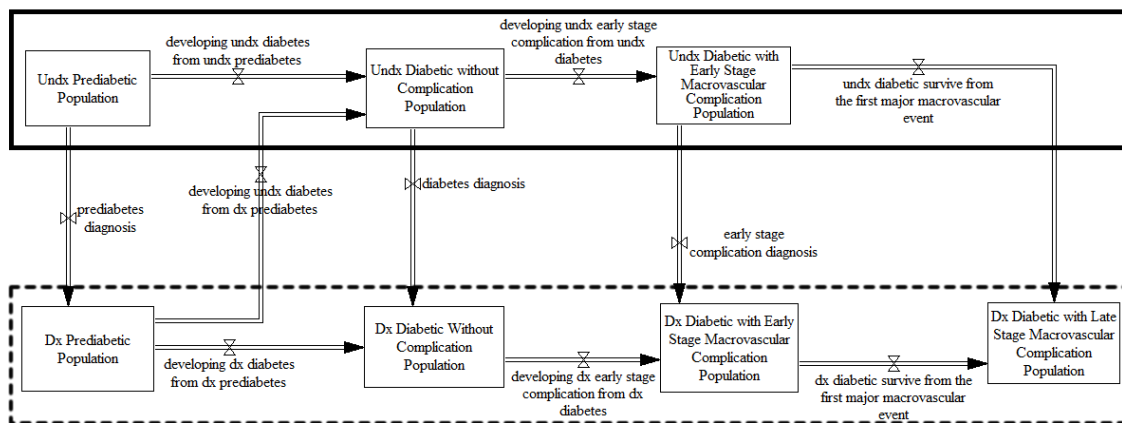


Figure 4-8. Development of Hyperglycemia

The hyperglycemic population is divided into undiagnosed population stocks and diagnosed population stocks based on the diagnosis of hyperglycemia. The three stocks in the solid box in Figure 4-8, the *Undx Prediabetic Population* stock, the *Undx Diabetic without Complication Population* stock and the *Undx Diabetic with Early Stage Complication*

Population stock, are the undiagnosed hyperglycemic population stocks. The four stocks that are enclosed by the dashed box are the diagnosed hyperglycemic population stocks: the *Dx Prediabetic Population* stock, the *Dx Diabetic without Complication Population* stock, the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock and the *Dx Diabetic with Late Stage Macrovascular Complication Population* stock. Each undiagnosed population stock has a diagnosis flow that moves parts of the population to a corresponding diagnosed population stock once the hyperglycemia or related complications are diagnosed. For example, the population moves from the *Undx Diabetic without Complication Population* stock to the *Dx Diabetic without Complication Population* stock once diabetes is diagnosed and the population moves from the *Undx Diabetic with Early Stage Macrovascular Complication Population* stock to the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock after any diabetes related complication is diagnosed. The only exception is that the *Dx Diabetic with Late Stage Macrovascular Complication Population* stock does not have a corresponding undiagnosed population stock due to the presence of obvious symptoms from late stage macrovascular complications. As a consequence, I assumed that all patients with late stage macrovascular complications are diagnosed.

The population in the section “hyperglycemic population” is also classified according to the progression of disease criterion into prediabetic population stocks, diabetic without complication population stocks, diabetes with early stage macrovascular complication population stocks and the diabetes with late stage macrovascular population stock. Population stocks in these four diabetes progress stages clearly separate the hyperglycemic population according to the progression of hyperglycemia.

Starting from the prediabetes stage, part of the population develops mild hyperglycemia. According to the WHO diabetes classification, a person whose blood glucose level is higher than in normoglycemia but which does not meet criteria of diabetes is prediabetic. The *Undx Prediabetic Population* stock and the *Dx Prediabetic population* stock in Figure 4-8 belong to this stage. The *Undx Prediabetic Population* stock has an incoming flow from each of the

normoglycemic population stocks. These incoming flows represent the population that develops prediabetes from the normal weight general population, the overweight general population and the obese general population.

The prediabetic population has a risk of developing more serious hyperglycemia and becoming diabetic. Hence, each prediabetic population stock has a progression flow, which connects to its corresponding diabetic without complication population stock. The prediabetic population moves to the diabetes without complication stage and maintains the status of diagnosis through the progression flow. Moreover, the *Dx Prediabetic Population* stock has another progression flow that connects to the *Undx Diabetic Population* stock. Diabetes is a chronic disease and it has a gradual onset progress. Patients developing diabetes from prediabetes may not be diagnosed with diabetes even if they were diagnosed with prediabetes previously. The flow from the *Dx Prediabetic Population* stock to the *Undx Diabetic Population* stock represents this progress.

The population in the *Dx Prediabetic Population* stock has a chance to recover from hyperglycemia and return to normoglycemic stage. The *Dx Prediabetic Population* stock has three recovery flows that return population back to the *Normal General Population*, the *Overweight General Population*, and the *Obese General Population* stocks.

The diabetes without complication stage is the next diabetes progress stage after the prediabetes stage. In the diabetes without complication stage, hyperglycemic patients have blood glucose levels higher than the criteria of diabetes, but have not yet developed any diabetes related complications. Some mild diabetic symptoms, such as blurry vision, increased thirst and itchy skin occur during this stage. The *Undx Diabetic without Complication Population* stock and the *Dx Diabetic without Complication Population* stock in Figure 4-8 belong to this stage. Each stock in this stage connects to a corresponding stock in the diabetes with early stage macrovascular complication stage by a diabetes progression flow. The hyperglycemic population in the diabetes without complication stage flows to the next stage, the diabetes with early stage macrovascular complication stage, once they develop any diabetes related

macrovascular complication.

Unlike these prediabetic population stocks, the population stocks in the diabetes without complication stage and further diabetes progression stages do not have a recovery flow, which returns population back to the normoglycemia stage. Diabetes is a life-long disease and currently there is no cure for it. People who developed diabetes will stay in a diabetic population stock but will not return to a normoglycemic population stock.

The next stage in diabetes progression is the diabetes with early stage macrovascular complication stage. In this stage, diabetic patients start to develop macrovascular diseases caused by diabetes, such as coronary diseases and cerebrovascular disease. The *Undx Diabetic with Early Stage Macrovascular Complication Population* stock and the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock in Figure 4-8 belong to this stage. Starting from this stage, I assume that all diabetic patients are diagnosed with diabetes. Based on this assumption, I define the population in the *Undx Diabetic with Early Stage Macrovascular Complication Population* stock as diagnosed with diabetes but not diagnosed with macrovascular complication.

Similar to population stocks in the diabetes without complication stage, population stocks in the diabetes with early stage macrovascular complication stage have a progression flow to the next and the last diabetes progression stage – the diabetes with late stage macrovascular complication stage. Progression flows from both the *Undx Diabetic with Early Stage Macrovascular Complication Population* stock and the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock connect to the *Dx Diabetic with Late Stage Macrovascular Complication Population* stock, the only population stock in the last diabetes progression stage.

The population in the final diabetes progression stage is the population who survived from the first attack of diabetes related macrovascular diseases, such as a heart attack or stroke. After the first attack of macrovascular diseases, any undiagnosed macrovascular complication are assumed manifest itself; hence, there is no undiagnosed population stock represented in the

final stage. Diabetic patients stay in this stage until their death.

Similar to other population stocks in the model, populations in the hyperglycemic population stocks are further divided according to age group, ethnic group and gender group using subscripts. Aging flows connect all age group stocks from the youngest to the oldest stock, forming an aging chain. Also, each population stock in the section “hyperglycemic population” has one or more death flows. These death flows move the population out the system. I will explain death flows in detail later.

The *Undx Prediabetic Population* stock is the first stock in the section “hyperglycemic population”. All hyperglycemic patients develop prediabetes without diagnosis first. The dynamics of this population stock are controlled by several incoming flows and outgoing flows. Equation 4.10 shows the mathematical formulation,

$$\begin{aligned}
 & \textit{Undx Prediabetic Population}(T) \\
 &= \int_0^T [\textit{developing prediabetes from normal weight} \\
 &+ \textit{developing prediabetes from overweight} \\
 &+ \textit{developing prediabetes from obese} \\
 &- \textit{undx prediabetic dying all causes} \\
 &- \textit{developing undx diabetes from undx prediabetes} \\
 &- \textit{prediabetes diagnosis + undx prediabetic population aging} \\
 &- \textit{undx prediabetic population aging}]dt ,
 \end{aligned}
 \tag{4.10}$$

where all positive parameters are incoming flows and all negative parameters are outgoing flows. All parameters in Equation 4.10 have age groups, gender groups and ethnic groups that are presented in subscripts.

I was not able to find a data source that allowed me to directly find the initial value for the *Undx Prediabetic Population* stock. I calculated and calibrated the initial value based on

the initial value of the *Dx Prediabetic Population* stock. The initial value of the *Dx Prediabetic Population* stock is calculated based on the initial value of *Dx Diabetic without Complication Population* stock. I assumed that the diagnosed prediabetic population has the same distribution as the diagnosed diabetic without complication population, but the diagnosed prediabetic population is 10 years younger than the diagnosed diabetic without complication population. Therefore, the initial value of the *Dx Prediabetic Population* stock is the product of the diagnosed diabetic population shifted by 10 years and a diabetes to prediabetes coefficient,

$$\begin{aligned}
 & \textit{init dx prediabetic population}[\textit{age group}] \\
 & \quad = \textit{init dx diabetic without complication}[\textit{age group} - 10] \\
 & \quad * \textit{init diabetes to prediabetes coefficient},
 \end{aligned}
 \tag{4.11}$$

where the diabetes to prediabetes coefficient is set to 1 initially and calibrated later.

After the initial value of the *Dx Prediabetic Population* stock is calculated, the initial value of the *Undx Prediabetic Population* stock is obtained from the product of the initial value of the *Dx Prediabetic Population* stock and several coefficients that reflect age, ethnicity and gender,

$$\begin{aligned}
 & \textit{init undx prediabetic population} \\
 & \quad = \textit{init dx prediabetic population} * \textit{init undx prediabetic age coefficient} \\
 & \quad * \textit{init undx prediabetic ethnic coefficient} \\
 & \quad * \textit{init undx prediabetic gender coefficient},
 \end{aligned}
 \tag{4.12}$$

where all coefficients are set to 1 initially and adjusted through calibration.

An undiagnosed prediabetic patient could develop diabetes without diagnosis. The flow *developing undx diabetes from undx prediabetes* in the model represents this progress. This progression flow moves people to the *Undx Diabetic without Complication Population*

stock when they develop diabetes. The rate of flow (in persons per year) is the quotient obtained by dividing the population in the *Undx Prediabetic Population* stock by the constant *avg years to develop diabetes from undx prediabetes*.

$$\begin{aligned} & \textit{developing undx diabetes from undx prediabetic} \\ &= \frac{\textit{Undx Prediabetic Population}}{\textit{avg years to develop diabetes from undx prediabetes}} \end{aligned} \tag{4.13}$$

Equation 4.13 is for the calculation of the *developing undx diabetes from undx prediabetes* flow rate. The value of the *avg years to develop diabetes from undx prediabetes* parameter is set to 10 years initially, and is calibrated against historical data. The calibration process will be described in the next chapter.

The *Undx Prediabetic Population* stock also has a diagnosis flow, the *prediabetes diagnosis*, that moves population to the *Dx Prediabetic Population* stock when their prediabetes is diagnosed. After undiagnosed prediabetic people receive a blood glucose test, their hyperglycemia may be diagnosed by doctors. Once the hyperglycemia is diagnosed, they move from the *Undx Prediabetic Population* stock to the *Dx Prediabetic Population* stock through the diagnosis flow.

I could not find reliable data sources for the prediabetes diagnosis rate for the SHR; hence, I use data and calculation from the CDC model. The prediabetes diagnosis rate is calculated based on the fraction of prediabetes detected by two relevant tests FPGT and OGTT (see Chapter 2), the average time between screenings and the sensitivity of FPGT and OGTT for detecting prediabetes. Equations from 4.14 to 4.19 below show the calculation steps for the prediabetes diagnosis rate and all constants are listed in Appendix B.

$$\begin{aligned}
& \text{avg time between screenings for high risk asymptomatic population} \\
& = \text{base time between screenings for high risk asymptomatic population} \\
& * \text{time between screenings coefficient for high risk asymptomatic age groups} \\
& * \text{time between screening coefficient for high risk asymptomatic ethnic groups} \\
& * \text{time between screening coefficient for high risk asymptomatic gender groups.}
\end{aligned}
\tag{4.14}$$

$$\begin{aligned}
& \text{avg sensitvity of screenings for IGT or IFG} \\
& = \text{sensitivity of OGTT screening for IGT or IFG} \\
& * \text{fraction of asymptomatic high risk screening using OGTT} \\
& + \text{sensitivity of FPGT screening for IFG} \\
& * (1 - \text{fraction of asymptomatic high risk screening using OGTT}).
\end{aligned}
\tag{4.15}$$

$$\begin{aligned}
& \text{avg time to next screening for undiagnosed prediabetic population} \\
& = \text{avg time between screeings for high risk asymptomatic population} \\
& * (0.5 * \text{avg sensitivity of screenings for IGT or IFG} + 1 \\
& * (1 - \text{avg sensitivity of screenings for IGT or IFG})).
\end{aligned}
\tag{4.16}$$

$$\begin{aligned}
& \text{detectable fraction of prediabetic population} \\
& = \text{fraction of prediabetic detectable by OGTT} \\
& * \text{fraction of asymptomatic high risk screenings using OGTT} \\
& + \text{fraction of prediabetic detectable by FPGT} \\
& * (1 - \text{fraction of asymptomatic high risk screenings using OGTT}).
\end{aligned}
\tag{4.17}$$

$$\begin{aligned}
& \text{detectable prediabetic population} \\
& = \text{prediabetic population} \\
& \quad * \text{detectable fraction of prediabetic population.}
\end{aligned}
\tag{4.18}$$

$$\begin{aligned}
& \text{prediabetes diagnosis} \\
& = \text{MAX} \left(0, \text{detectable prediabetic population} \right. \\
& \quad * \text{ever screened fraction of high risks} - \text{dx prediabetic population} \\
& \quad \left. * \frac{\text{avg sensitivity of screens for IGT or IFG}}{\text{avg time to next screening for undiagnosed prediabetic population}} \right).
\end{aligned}
\tag{4.19}$$

The death flow rate for the *Undx Prediabetic Population* stock is the product of the population in the stock and mortality rate of the undiagnosed prediabetic population.

$$\begin{aligned}
& \text{undx prediabetic dying all causes} \\
& = \text{undx prediabetic population} \\
& \quad * \text{controlled mortality for undx prediabetic population.}
\end{aligned}
\tag{4.20}$$

I do not have mortality rates for the undiagnosed prediabetic population. I assumed the mortality rate of the undiagnosed prediabetic population would be close to the mortality rate of the obese general population since hyperglycemia has not yet done any serious damage. Hence, I applied the mortality rate of the obese general population in the calculation.

The aging flow of the *Undx Prediabetic Population* stock is the exactly same as aging flows for other population stocks. The incoming aging flow is set to 0 for the *Age Group 0 to 4* group since it is the youngest age group in the model; and the outgoing aging flow is set to 0 for the *Age group 80 plus* group since it is the oldest age group in the system.

The *Dx Prediabetic Population* stock is the diagnosed population stock in the prediabetes stage. After prediabetes is diagnosed, prediabetic patients move from the *Undx Prediabetic Population* stock to the *Dx Prediabetic Population* stock. The population in this stock is controlled by several incoming flows and outgoing flows.

Dx Prediabetic Population(T)

$$\begin{aligned}
 &= \int_0^T [\textit{prediabetes diagnosis} - \textit{dx prediabetic dying all causes} \\
 &\quad - \textit{normal weight prediabetes recovery} \\
 &\quad - \textit{overweight prediabetes recovery} - \textit{obese prediabetes recovery} \\
 &\quad - \textit{developing undx diabetes from dx prediabetic} \\
 &\quad - \textit{developing dx diabetes from dx prediabetic} - \textit{dx prediabetic aging} \\
 &\quad + \textit{dx prediabetic aging}]dt.
 \end{aligned}$$

(4.21)

Equation 4.21 shows the mathematical formulation. Like other stocks, all parameters in the equation include implicit age, gender and ethnicity subscripts.

The initial value for the *Dx Prediabetic Population* stock is calculated by shifting the initial value of the *Dx Diabetic without Complication* stock by 10 years. A similar calculation for the initial value of the *Undx Prediabetic Population* stock was described above.

The population in the *Dx Prediabetic Population* has the potential for recovering from prediabetes and returning back to a normoglycemia state. Three recovery flows, the *normal weight prediabetes recovery*, the *overweight prediabetes recovery* and the *obese prediabetes recovery* represent the recovery progress. The equation

$$\begin{aligned}
& \textit{normal weight prediabetes recovery} \\
& = \textit{Dx Prediabetic Population} \\
& * \textit{prediabetes recovery rate[normal weight]}
\end{aligned}
\tag{4.22}$$

characterizes the mathematical representation of the recovery progress for the normal weight population, and equations for the overweight and the obese population are essentially the same. Prediabetes recovery rates are set to 0, 0.03 and 0 for the normal weight, the overweight and the obese population respectively.

The *developing dx diabetes from dx prediabetic* flow is one of the two progression flows initialized from the *Dx Prediabetic Population* stock. This flow represents the progression by which the diagnosed prediabetic population develops diabetes and where diabetes is diagnosed soon after onset (for example, due to close ongoing management of the prediabetes). The rate of this flow is controlled by the population in the *Dx Prediabetic Population* stock and two parameters: the *avg years to develop diabetes from dx prediabetes* and the *fraction developing diabetes without diagnosis*; as equation 4.23 shows below. The *fraction developing diabetes without diagnosis* is set to 0.1 initially, and its value is adjusted by calibration. The *avg years to develop diabetes from dx prediabetes* is the product of the *avg years to develop diabetes from undx prediabetes* and the *dx diabetes progress coefficient*. The *dx diabetes progress coefficient* is set to 1.5 initially since it usually takes longer to develop diabetes if the prediabetic patient is diagnosed and with good management; this coefficient is then calibrated against historical data.

$$\begin{aligned}
& \textit{developing dx diabetes from dx prediabetic} \\
& = \frac{\textit{Dx Prediabetic Population}}{\textit{avg years to develop diabetes from dx prediabetes}} \\
& * (1 - \textit{fraction developing diabetes with diagnosis}).
\end{aligned}
\tag{4.23}$$

The *developing undx diabetes from dx prediabetic* is another progression flow that is

initialized from the *Dx Prediabetic Population* stock. Some prediabetic patients do not check with a doctor even after they are diagnosed. Their hyperglycemia can become worse without notice and new conditions are undiagnosed. This part of population moves to the undiagnosed diabetes stock when they progress to the next stage. The *developing undx diabetes from dx prediabetic* flow moves these patients from the *Dx Prediabetic Population* stock to the *Undx Diabetic without Complication Population* stock. Similar to the *developing dx diabetes from dx prediabetic* flow, the rate of the *developing dx diabetes from dx prediabetic* flow is determined by the population in the *Dx Prediabetic Population* stock, the *avg years to develop diabetes from dx prediabetes* and the *fraction developing diabetes without diagnosis*.

$$\begin{aligned}
 & \textit{developing dx diabetes from dx prediabetic} \\
 &= \frac{\textit{Dx Prediabetic Population}}{\textit{avg years to develop diabetes from dx prediabetes}} \\
 & * (\textit{fraction developing diabetes with diagnosis}).
 \end{aligned}
 \tag{4.24}$$

The death flow for the *Dx Prediabetic Population* stock is the *dx prediabetic dying all causes*. The rate of this death flow is the product of the population in the stock and mortality rate of the undiagnosed prediabetic population. Equation 4.25 below shows the calculation. I applied the mortality of the Obese General Population stock here since I do not have any data for the mortality of the prediabetic population in the SHR.

$$\begin{aligned}
 & \textit{dx prediabetic dying all causes} \\
 &= \textit{dx prediabetic population} \\
 & * \textit{controlled mortality for dx prediabetic population}.
 \end{aligned}
 \tag{4.25}$$

The *Dx Prediabetic Population* stock has the same aging chain structure as other

population stocks that are connected by aging flows.

The *Undx Diabetic without Complication Population* stock is the undiagnosed population stock in the diabetes without complication progression stage. Hyperglycemic patients in this stock have developed diabetes but have not developed any diabetes related complication, and the hyperglycemic condition remains undiagnosed. Several incoming flows and outgoing flows together create the dynamics of the *Undx Diabetic without Complication Population* stock. Equation 4.26 shows the mathematical formation. Each positive parameter represents an incoming flow and each negative parameter represents an outgoing flow in the integration. Corresponding to the population in the stock, each flow is also associated with age groups, gender groups and ethnic groups that are represented by subscripts.

Undx Diabetic without Complication Population(T)

$$\begin{aligned}
 &= \int_0^T [developing undx diabetes from undx prediabetic \\
 &+ developing undx diabetes from dx prediabetic - diabetes diagnosis \\
 &- developing undx early stage complication from undx diabetic \\
 &- undx diabetic without complication dying all causes \\
 &- undx diabetic without complicaiton population aging \\
 &+ undx diabetic without complication population aging]dt.
 \end{aligned}$$

(4.26)

The initial value of the *Undx Diabetic without Complication Population* stock is calibrated based on the initial value of the *Dx Diabetic without Complication Population* stock. I do not have any reliable source for the undiagnosed diabetic without any complication population. Hence, I first calculated the total diagnosed diabetic population in the SHR from the total covered population in the SHR and the diabetes prevalence among the Saskatchewan population [61, 62]. Here I made the assumption that population in the SHR has the same

diabetes prevalence as Saskatchewan population. After the total diagnosed diabetic population is obtained, I calculated the initial value of the *Dx Diabetic without Complication Population* stock from the total diagnosed diabetic population by using an estimated percentage of diabetic patients without any complication [63]. The initial value of the *Undx Diabetic without Complication Population* stock is set to the product of the initial value of the *Dx Diabetic without Complication Population* and three coefficients that reflect age, ethnicity and gender. By adjusting these three coefficients to match historical data, I find the best fit data for the initial value of the *Undx Diabetic without Complication Population* stock.

$$\begin{aligned}
 & \textit{init Undx Diabetic without Complication Population} \\
 & = \textit{init Dx Diabetic without Complication Population} \\
 & \quad * \textit{init undx diabetic without complication population age coefficient} \\
 & \quad * \textit{init undx diabetic without complication population gender coefficient} \\
 & \quad * \textit{init undx diabetic without complicaiton population ethnic coefficient.}
 \end{aligned}
 \tag{4.27}$$

The *Undx Diabetic without Complication Population* stock has a diagnosis flow, the *diabetes diagnosis*, which moves diabetic patients to the *Dx Diabetic without Complication Population* stock after their diabetic condition is diagnosed. Ideally, the rate of this flow should be set to a fraction of the incidence of diabetes in the SHR since the incidence of diabetes is the combined rate of the *diabetes diagnosis*, the *developing dx diabetes from dx prediabetes* and the *developing undx early stage complication from undx diabetic* flows. Although I have data for the incidence in the SHR, I do not know what fraction of the different flows. As a fallback, I adapted the diabetes diagnosis calculation from the CDC model as the initial value and calibrated the result with the historical data of incidence in the SHR. Equations 4.28 to 4.32 below are for the calculation of the flow rate of the *diabetes diagnosis*. Some parameters were calculated previously for the prediabetes diagnosis rate. All constant values are listed in

Appendix B.

Diabetes Diagnosis

$$\begin{aligned} &= \text{MAX}(0, \text{detectable diabetes without complication population} \\ & * \text{ever screened fraction of high risk} \\ & - \text{Dx Diabetic without Complication Population}) \\ & * \frac{\text{avg sensitivity of screen for diabetes without complication}}{\text{avg time to next screening for diabetes without complication}} \end{aligned} \quad (4.28)$$

detectable diabetes without complication population

$$\begin{aligned} &= (\text{Dx Diabetic without Complication Population} \\ & + \text{Undx Diabetic without Complication Population}) \\ & * \text{detectable fraction of diabetes without complication.} \end{aligned} \quad (4.29)$$

detectable fraction of diabetes without complication

$$\begin{aligned} &= \text{fraction of diabetes detectable by OGTT} \\ & * \text{fraction of asymptomatic high risk screenings using OGTT} \\ & + \text{fraction of diabetes detectable by FPGT} \\ & * (1 - \text{fraction of asymptomatic high risk screenings using OGTT}). \end{aligned} \quad (4.30)$$

$$\begin{aligned}
& \text{avg time to next screening for diabetes without complication} \\
& = \text{avg time between screenings for high risk asymptomatic population} \\
& * (0.5 * \text{avg sensitivity of screening for diabetes without complication} \\
& + 1 \\
& * (1 - \text{avg sensitivity of screening for diabetes without complication})).
\end{aligned}
\tag{4.31}$$

$$\begin{aligned}
& \text{avg sensitivity of screening for diabetes without complication} \\
& = \text{sensitivity of OGTT screening for diabetes} \\
& * \text{fraction of asymptomatic high risk screenings using OGTT} \\
& + \text{sensitivity of FPGT screening for diabetes} \\
& * (1 - \text{fraction of asymptomatic high risk screenings using OGTT}).
\end{aligned}
\tag{4.32}$$

Besides the diagnosis flow, the *Undx Diabetic without Complication Population* stock has a progression flow, the *developing undx early stage complication from undx diabetic*. This flow moves population to the next progression stage when the diabetic condition becomes worse and an individual develops diabetes related macrovascular complications. I made the assumption that the diabetic population in the *Undx Diabetic with Early Stage Complication Population* stock is diagnosed with diabetes but is not diagnosed with diabetes related complication. Thus, an individual moving to the next progression stage through this flow will be diagnosed with diabetes. Hence, this flow can be seen as a diagnosis flow as well.

Equation

$$\begin{aligned}
& \text{developing undx early stage complication from undx diabetic} \\
& = \frac{\text{Undx Diabetic without Complication Population}}{\text{avg years to develop early stage complication from undx diabetic}}
\end{aligned}
\tag{4.33}$$

shows that the rate of the *developing undx early stage complication from undx diabetic* flow is controlled by the population in the *Undx Diabetic without Complication Population* stock and the constant parameter *avg years to develop early stage complication from undx diabetic*. The value of the constant parameter was set to 10 initially, and calibrated by matching a historical data set. The calibration process will be explained in the next chapter.

The population in the *Undx Diabetic without Complication Population* stock that is dying for any reason flows out the system through the *undx diabetic without complication dying all causes* flow. The death flow is calculated using equation

$$\begin{aligned}
 & \textit{undx diabetic without complication dying all causes} \\
 & = \textit{Undx Diabetic without Complication Population} \\
 & * \textit{Mortality of undx diabetic without complicaiton population},
 \end{aligned}
 \tag{4.34}$$

where the *mortality of undx diabetic without complication population* is calibrated using the average mortality of the diabetic population and a calibration coefficient.

Like other population stocks in the system, the population in the *Undx Diabetic without Complication Population* stock is grouped into age groups using subscripts. Age groups are linked by aging flows and form an aging chain. Equations for aging flows for the *Undx Diabetic without Complication Population* stock are the similar to those for aging flows associated with other population stocks.

During the diabetes without complication stage, undiagnosed diabetic patients can be diagnosed by medical practitioners. These diabetic patients become diagnosed patients and move to the *Dx Diabetic without Complication Population* stock. The population in the stock is influenced by three incoming flows and three outgoing flows, as indicated by the following equation

Dx Diabetic without Complication Population(T)

$$\begin{aligned}
 &= \int_0^T [\textit{developing dx diabetes from dx prediabetic} + \textit{diabetes diagnosis} \\
 &\quad - \textit{dx diabetic without complication dying all causes} \\
 &\quad - \textit{developing dx early stage complication from dx diabetic} \\
 &\quad - \textit{dx diabetic without complication aging} \\
 &\quad + \textit{dx diabetic without complication aging}]dt.
 \end{aligned}
 \tag{4.35}$$

In the equation, the *developing dx early stage complication from dx diabetic* is the progression flow and the *dx diabetic without complication dying all causes* is the death flow that associated with the *Dx Diabetic without Complication Population* stock.

The initial value of the *Dx Diabetic without Complication Population* stock is calculated based on the estimated total diabetic population in the SHR and ratio of diabetic population without complication in total diabetic population from Morgan *et al.*[63]. The initial value is listed in Appendix A.

The progression flow, the *developing dx early stage complication from dx diabetic*, associated with the *Dx Diabetic without Complication Population* stock and moves population to the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock when a diabetic patient develops diabetes related macrovascular complication. The rate of this progression flow is calculated from

$$\begin{aligned}
 &\textit{developing dx early stage complication from dx diabetic} = \\
 &\quad \frac{\textit{Dx Diabetic without Complication Population}}{\textit{avg years to develop early stage complication from dx diabetes}} ,
 \end{aligned}
 \tag{4.36}$$

where the *avg years to develop early stage complication from dx diabetes* parameter was set to 15 years initially and adjusted through calibration.

The population in the *Dx Diabetic without Complication Population* stock who is dying from any cause flows out the stock through the *diabetic without complication dying all causes* flow. The rate of the *diabetic without complication dying all causes* flow depends on the mortality rate of the diagnosed diabetic without complication population in the SHR. I do not have data that shows mortality just for diagnosed diabetic without complication population. Hence, I set the mortality of the diagnosed diabetic without complication population to the product of the mortality of the undiagnosed diabetic without complication population and a coefficient reflecting the diagnosed diabetic without complication population, then calibrate the coefficient to estimate a better value for both the mortality of the diagnosed diabetic without complication population and the mortality of the undiagnosed diabetic without complication population.

$$\begin{aligned}
 & \textit{mortality of dx diabetic without complication population} \\
 & = \textit{mortality of undx diabetic without complication population} \\
 & \quad * \textit{mortality coefficient dx diabetic without complication.}
 \end{aligned}
 \tag{4.37}$$

The aging flows for the *Dx Diabetic without Complication Population* stock have the same structure as aging flows for other population stocks. With the exception of the oldest age group, a part of population in an age group flows to the next age group every year.

After years of diabetes, high levels of blood glucose damage patients' organs, nervous systems and blood vessels systems over time. Impaired organs, nervous systems and blood vessels cause diabetes related complications, such as coronary artery disease, heart attack, stroke, neuropathy, nephropathy and retinopathy. These complications – and especially macrovascular complication – are the real killers of most diabetes patients, not the high level of blood glucose. Once diabetic patients develop any macrovascular complication, they move to the next diabetes progression stage, the diabetic with early stage complication phase. If the new development of

macrovascular complication is not diagnosed, these part of patients flow to the *Undx Diabetic with Early Stage Macrovascular Complication Population* stock.

The population in the *Undx Diabetic with Early Stage Macrovascular Complication Population* stock is calculated by using

$$\begin{aligned}
 & \text{Undx Diabetic with Early Stage Macrovascular Complication Population}(T) \\
 &= \int_0^T [\text{developing undx early stage complication from undx diabetic} \\
 & - \text{undx diabetic with early stage complication dying all causes} \\
 & - \text{undx diabetic with early stage complication dying onset of the first major event} \\
 & - \text{diabetes with early stage complication diagnosis} \\
 & - \text{undx diabetic survive from the first major macrovascular complication event} \\
 & + \text{undx diabetic with early stage complication population aging} \\
 & - \text{undx diabetic with early stage complication population aging}]dt,
 \end{aligned}
 \tag{4.38}$$

where *undx diabetic survive from the first major macrovascular complication event* is the progression flow to the next disease progression stage.

For the initial value of the *Undx Diabetic with Early Stage Macrovascular Complication Population* stock, I lack a direct data source that allows me to find the number of diabetic patients in the SHR that have undiagnosed early stage macrovascular complications. Hence, I calculated the estimated initial value of the *Undx Diabetic with Early Stage Macrovascular Complication Population* stock from the total number of diabetic patient with early stage macrovascular complication in the SHR and three coefficients that reflect the difference between undiagnosed and diagnosed diabetic with early stage macrovascular complication population according to age, ethnicity and gender. The calculation is defined as

$$\begin{aligned}
& \textit{init undx diabetic with early stage macrovascular complication population} \\
& = \textit{init total diabetic with early stage macrovascular complication population} \\
& * \textit{init undx diabetic with early stage complication population age coefficient} \\
& * \textit{init undx diabetic with early stage complication population ethnic coefficient} \\
& * \textit{init undx diabetic with early stage complication population gender coefficient,}
\end{aligned}
\tag{4.39}$$

where the *init undx diabetic with early stage complication population ethnic coefficient* is set to 0.1 for both ethnic groups and *init undx diabetic with early stage complication population gender coefficient* are set to 0.1 for both gender groups initially. To reduce the dimensionality of the parameter space searched during calibration, the *init undx diabetic with early stage macrovascular complication age coefficient* is made up of two separated coefficients; one for age from 0 to 49 and one for age 50 and up, rather than setting a value for each individual age group. The coefficient for the younger population, the *init undx diabetic with early stage complication youth coefficient*, is set to 0.5 initially. The coefficient for older population, the *init undx diabetic with early stage complication elderly coefficient*, is set to 0.1 initially. All coefficients are calibrated to better matching values during the calibration process.

If diabetic patients with undiagnosed macrovascular complications are diagnosed with macrovascular complications, this part of the undiagnosed population becomes the diagnosed population and flows to the *Dx Diabetic with Early Stage Complication Population* stock through the *diabetes with early stage complication diagnosis* flow. The rate of the *diabetes with early stage complication diagnosis* flow is calculated from the population in the stock and three coefficients as

$$\begin{aligned}
& \textit{diabetes with early stage complicaition diagnosis} \\
& = \textit{Undx Diabetic with Early Stage Macrovascular Complication Population} \\
& * \textit{early stage macrovascular complication diagnosis age coefficient} \\
& * \textit{early stage macrovascular complication diagnosis ethnic coefficient} \\
& * \textit{early stage macrovascular complication diagnosis gender coefficient,}
\end{aligned}
\tag{4.40}$$

where the *early stage macrovascular complication diagnosis ethnic coefficient* is set to 0.1 for both ethnic groups and *the early stage macrovascular complication diagnosis gender coefficient* is set to 0.1 for both gender groups. Similar to the *init diabetic with early stage complication age coefficient*, the *early stage macrovascular complication diagnosis age coefficient* is made up of two parts, one for age from 0 to 49 and one for age 50 and up. The one for younger age groups is set to 0 and the one for older age groups is set to 0.5 initially. These early stage macrovascular complication diagnosis coefficients are calibrated to more consistent values by matching historical data in the calibration process.

The population in the *Undx Diabetic with Early Stage macrovascular Complication Population* stock has a risk of attack from macrovascular complications, which are associated with high mortality. If people survive the first attack of any major macrovascular complication, this part of population moves to the *Dx Diabetic with Late Stage Macrovascular Complication Population* stock from the *Undx Diabetic with Early Stage Macrovascular Complication Population* stock through the *undx diabetic survive from the first major macrovascular complication event* progression flow. The flow rate of the *undx diabetic survive from the first major macrovascular complication event* is calculated as

$$\begin{aligned}
& \textit{undx diabetic survive from the first major macrovascular complication event} \\
& = \textit{Undx Diabetic with Early Stage Macrovascular Complication Population} \\
& * (1 - \textit{Mortality of diabetic major macrovascular complication}).
\end{aligned}
\tag{4.41}$$

The *Undx Diabetic with Early Stage Macrovascular Complication Population* stock has two death flows. The first death flow *undx diabetic with early stage complication dying onset of the first major event* is for people dying from the onset of the first major macrovascular event, like acute myocardial infarction (AMI, commonly known as a “heart attack”) and stroke. I separate the population dying from the first major macrovascular complication event from the general death flow since the mortality for major macrovascular complication event is very high. The population flow out through this flow is calculated as

$$\begin{aligned}
 & \textit{undx diabetic with early stage complication dying onset of the first major event} \\
 & = \textit{Undx Diabetic with Early Stage Macrovascular Complication Population} \\
 & * \textit{mortality of diabetic major macrovascular complication.}
 \end{aligned}
 \tag{4.42}$$

The *mortality of diabetic major macrovascular complication* is obtained by combining the mortality of first-ever AMI onset and the mortality of first-ever stroke onset as

$$\begin{aligned}
 & \textit{mortality of diabetic major macrovascular complication} \\
 & = \textit{first ever AMI mortality} \\
 & * \textit{first ever AMI onset rate for diabetic population} \\
 & + \textit{first ever stroke mortality} \\
 & * \textit{first ever stroke onset rate for daibetic population.}
 \end{aligned}
 \tag{4.43}$$

The value of the *first ever AMI mortality* is obtained from “*Outcomes of acute myocardial infarction in Canada*” [70] and the value of the *first ever AMI onset rate for diabetic population* is obtained from “*Alberta Diabetes Atlas*” [64]. The value of the *first ever stroke mortality* is obtained from “*Incidence, comorbidity, case fatality and readmission of hospitalized stroke*

patients in Canada” [71] and the value of the *first ever stroke onset rate for diabetic population* is obtained from “*Alberta Diabetes Atlas*” [64].

The second death flow *undx diabetic with early stage complication dying all causes* is for people that are dying from all other causes except macrovascular complication major events. Similar to the situation with other general death flows, the rate of the *undx diabetic with early stage complication dying all causes* flow is determined by the mortality of the undiagnosed diabetic with early stage complication population as

$$\begin{aligned}
 & \textit{undx diabetic with early stage complication dying all causes} \\
 & = \textit{Undx Diabetic with Early Stage Complication Population} \\
 & * \textit{all other causes mortality of undx diabetic with early stage complication population.}
 \end{aligned}
 \tag{4.44}$$

I do not have data for the all other causes except macrovascular major event mortality of the undiagnosed diabetic with early stage macrovascular complication population; hence, I calculated this mortality from the mortality of the undiagnosed diabetic without complication population by applying a coefficient that reflects the difference between two mortalities. The mathematical notation is defined as

$$\begin{aligned}
 & \textit{all other causes mortality of undx diabetic with early stage complication population} \\
 & = \textit{mortality of undx diabetic without complication population} \\
 & * \textit{mortality coefficient undx diabetic with early stage complication,}
 \end{aligned}
 \tag{4.45}$$

where the *mortality coefficient undx diabetic with early stage complication* is a constant greater than 1. The value of the mortality coefficient is set to 1.2 initially, and it is adjusted in the calibration process.

Like all population stocks in the model, the *Undx Diabetic with Early Stage*

Complication Population stock is disaggregated using subscripts according to age groups, ethnic groups and gender groups. Moreover, aging flows between age groups move people to older age groups and form an aging chain structure.

If diabetic patients with undiagnosed early stage macrovascular complications are diagnosed with macrovascular complication before the first major attack, they move to the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock. The population in this stock is calculated as

$$\begin{aligned}
 & Dx \text{ Diabetic with Early Stage Macrovascular Complication Population}(T) \\
 &= \int_0^T [\textit{developing dx early stage complication from dx diabetic} \\
 &\quad - \textit{dx diabetic with early stage complication dying all other causes} \\
 &\quad - \textit{dx diabetic with early stage complication dying onset of the first major event} \\
 &\quad + \textit{diabetes with early stage complication diagnosis} \\
 &\quad - \textit{dx diabetic survive from the first major macrovascular complication event} \\
 &\quad - \textit{dx diabetic with early stage complication population aging} \\
 &\quad + \textit{dx diabetic with early stage complication population aging}]dt,
 \end{aligned}
 \tag{4.46}$$

where positive parameters represent incoming flows and negative parameters represent outgoing flows.

The initial population in the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock is calculated backward from the total diabetic population in the SHR. First, I obtained the total diabetic population with early stage macrovascular complications from the total diagnosed diabetic population by removing the diagnosed diabetic without complication population and diagnosed diabetics who have experienced their first major macrovascular complication event. Second, I use three coefficients according to age, ethnicity and gender that reflect difference between the undiagnosed and the diagnosed diabetic with early stage

macrovascular complication. These coefficients separate the undiagnosed and diagnosed diabetic population from the total diabetic with early stage macrovascular complication population.

$$\begin{aligned}
 & \textit{init dx diabetic with early stage macrovascular complication population} \\
 & = \textit{init total diabetic with early stage macrovascular complication population} \\
 & * (1 - \textit{init undx diabetic with early stage complication population age coefficient}) \\
 & * (1 - \textit{init undx diabetic with early stage complication population ethnic coefficient}) \\
 & * (1 \\
 & - \textit{init undx diabetic with early stage complication population gender coefficient}).
 \end{aligned}
 \tag{4.47}$$

The population in the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock also has a high risk of macrovascular complication major event. If diabetic patients survive from the first macrovascular complication major event, they move to the last progression stage: the diabetes with late stage macrovascular complication phase. The number of diabetic patients surviving from a macrovascular complication major event is determined by the mortality of the macrovascular complication event. The exact number of survivors is calculated as

$$\begin{aligned}
 & \textit{dx diabetic survive from the first major macrovascular complication event} \\
 & = \textit{Dx Diabetic with Early Stage Macrovascular Complication Population} \\
 & * (1 - \textit{mortality of diabetic major macrovascular complication}).
 \end{aligned}
 \tag{4.48}$$

If diabetic patients unfortunately do not survive from the first major macrovascular complication event, this part of population flows out the system through the *dx diabetic with*

early stage macrovascular complication dying onset of the first major event death flow. The mathematical notation for this death flow is defined as

$$\begin{aligned}
 & \textit{dx diabetic with early stage complication dying onset of the first major event} \\
 & = \textit{Dx Diabetic with Early Stage Macrovascular Complication Population} \\
 & * \textit{mortality of diabetic major macrovascular complication.}
 \end{aligned}
 \tag{4.49}$$

The *Dx Diabetic with Early Stage Macrovascular Complication Population* stock has another death flow, the *dx diabetic with early stage complication dying all other causes*, besides the *dx diabetic with early stage complication dying onset of the first major event* death flow. This flow represents the population in the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock dying of all causes except macrovascular complication major event. The rate of this death flow is calculated based on the population in the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock and the mortality *all other causes mortality of dx diabetic with early stage complication population*. The mathematical notation for the rate of the *dx diabetic with early stage complication dying all other causes* flow is defined as

$$\begin{aligned}
 & \textit{dx diabetic with early stage complication dying all other causes} \\
 & = \textit{Dx Diabetic with Early Stage Macrovascular Complication Population} \\
 & * \textit{all other causes mortality of dx diabetic with early stage complication population.}
 \end{aligned}
 \tag{4.50}$$

The value of the *all other causes mortality of dx diabetic with early stage complication population* is calculated based on the value of the *all other causes mortality of undx diabetic with early stage complication population* since I do not have any data to calculate it directly. Hence,

I define a coefficient to reflect the difference between the mortality of diagnosed and undiagnosed diabetic population and use this coefficient to calculate the value of the *all other causes mortality of dx diabetic with early stage complication population*.

all other causes mortality of dx diabetic with early stage complication population
 = *all other causes mortality of undx diabetic with early stage complication population*
 * *mortality coefficient dx diabetic with early stage complication*.

(4.51)

I assumed that the diabetic population with diagnosed complications has a lower mortality than the diabetic population with undiagnosed complication and that the coefficient is therefore less than 1. The value of coefficient is set to 0.9 initially and is adjusted in calibration in order to find a better value for the *all other causes mortality of dx diabetic with early stage complication population*.

The population in the *Dx Diabetic with Early Stage Macrovascular Complication Population* stock is grouped according to age, ethnicity and gender like other population stocks. Age groups in the diagnosed diabetic with early stage macrovascular complication population are connected by aging flows and form an aging chain.

The difference between the early stage macrovascular complication stage and the late stage macrovascular complication stage is that people in the late stage have survived from the first attack of major macrovascular complications. I assumed that patients in the late stage are hospitalized after their first macrovascular major event and their conditions are diagnosed. Hence, the *Dx Diabetic with Late Stage Macrovascular Complication Population* stock is the only stock in the late macrovascular complication stage; no corresponding undiagnosed stock exists. The population who has late stage of macrovascular complications is facing a very serious condition of diabetes related macrovascular complications. The mathematical equation for calculating population in the *Dx Diabetic with Late Stage Macrovascular Complication*

Population stock is defined as

$$\begin{aligned}
 & \text{Dx Diabetic with Late Stage Macrovascular Complication Population}(T) \\
 &= \int_0^T [dx \text{ diabetic survive from the first major macrovascular complication event} \\
 &+ undx \text{ diabetic survive from the first major macrovascular complication event} \\
 &- dx \text{ diabetic with late stage complication dying all causes} \\
 &+ dx \text{ diabetic with late stage complication aging} \\
 &- dx \text{ diabetic with late stage complicaiton aging}]dt.
 \end{aligned}
 \tag{4.52}$$

The initial population in the *Dx Diabetic with Late Stage Macrovascular Complication Population* stock is calculated based on the total diagnosed diabetic population in the SHR and ratio between the diabetic population that have experienced a macrovascular major event and the total diabetic population. First, I obtained the weighted number of diabetic patients who had macrovascular major event in Saskatchewan from a CCHS [72] dataset; and then I obtained the weighted number of diabetic patients in Saskatchewan from the same dataset. Secondly, I calculated the ratio of diabetic patients with a macrovascular major event and the total number of diabetic patients based on the number I found from the CCHS dataset. In the final step, I applied the ratio to the number of diabetic patients in the SHR to obtain the number of diabetic patients that had a macrovascular major event in the SHR. The initial number of diabetic patient having a macrovascular major event in the SHR is listed in Appendix A.

The *Dx Diabetic with Late Stage Macrovascular Complication Population* stock is associated with neither a progression flow nor a diagnosis flow. The diabetic patients in the *Dx Diabetic with Late Stage Macrovascular Complication Population* stock stay in the stock until they die since this is the last stock in the diabetes progression. The death flow *dx diabetic with late stage complication dying all causes* is controlled by the mortality of diagnosed diabetic with

late stage complication population. The mathematical formulation of this flow is as follows:

$$\begin{aligned}
 &dx \text{ diabetic with late stage complication dying all causes} \\
 &= Dx \text{ Diabetic with Late Stage Macrovascular Complication Population} \\
 &\quad * \text{ mortality of } dx \text{ diabetic with late stage complication population.}
 \end{aligned}
 \tag{4.53}$$

The mortality of the diagnosed diabetic with late stage complication population is calculated based on the *all other causes mortality of dx diabetic with early stage complication* and a coefficient that reflects the difference between two mortalities. The mathematical notation for the calculation is defined as

$$\begin{aligned}
 &\text{mortality of } dx \text{ diabetic with late stage complication population} \\
 &= \text{all other causes mortality of } dx \text{ diabetic with early stage complication population} \\
 &\quad * \text{ mortality coefficient } dx \text{ diabetic with late stage complication,}
 \end{aligned}
 \tag{4.54}$$

where the mortality coefficient *dx diabetic with late stage complication* is set to 1.2 since I know the population with late stage complication is facing higher risk than the population with early stage complication. The coefficient is fine tuned in the calibration process later.

The *Dx Diabetic with Late Stage Macrovascular Complication Population* stock has an aging chain structure just like other population stock in the model. The mathematical equations of the aging flows for the *Dx Diabetic with Late Stage Macrovascular Complication Population* stock are also similar to those applied for other aging flow.

4.3 Summary

In this chapter, I first reviewed the adaptation process of my model. Pioneering research in the diabetes modeling area created a solid foundation for starting my model. By adapting model structures from these pioneer models, I built my model that reflects the local environment.

After I reviewed the adaptation process, I went through the model structure in detail. First, I explained the “normoglycemic population” section in the model. This section simulates the dynamic in the population who do not have hyperglycemia and provides a population base for the hyperglycemic population since every hyperglycemic patient originated in this section before developing hyperglycemia. Second, I explained the “hyperglycemic population” section, the core section in my model. This section simulates the dynamic in the hyperglycemic population, which is the most important subject of my research. By observing dynamics in this section, I am able to evaluate impact from any endogenous and exogenous changes.

During the model parameterization, I could not find direct data for many parameters. In some cases I could only find data for other regions; in some cases I found aggregated data that is not separated by age, gender or ethnicity. In the worst situation, I could not find any data at all. In these situations, I disaggregated data by using factors and used calibration techniques find out the best values for these factors and unknown parameters. In the next chapter, I will explain the structure and process of calibrating the model.

CHAPTER 5

CALIBRATION

In the previous chapter, I mentioned the word “calibration” many times especially in cases I lacked data during parameterization. But what actually is calibration? Calibration is the action of adjusting experimental results to take external factors into account or to allow comparison with other data [65]. In the modeling world, calibration is the process that adjusting model parameters and finding an agreement between observed results and simulated results [66].

In this chapter, I will explain the basic concept of calibration in the modeling process. We will seek to provide an understanding how calibration makes use of historical data, discrepancy, weights and payoff in calibration. We will provide an explanation of what calibration offer in a modeling process.

After the basic concept of calibration, I will describe the calibration structure in my model and go through the calibration process in detail. First, I will describe the historical data that is used in my calibration and the discrepancy between historical data and model output. Secondly, I will explain the weighting structure employed in the calibration and the assignment of weights. Last but not the least, I will explain parameters that need to be adjusted in the calibration and their boundary settings.

In the last part of this chapter, I will explain key findings from the calibration process. As the most important result from the calibration, the model is able to match the trend of the historical data with a relatively small discrepancy after the calibration. Moreover, calibration is a very good tool for verifying model structure and data used in the model. During the calibration process, I improved the model structure and verified values of parameters in the model from unexpected discrepancies and abnormal outputs. I will describe these improvements in the chapter as well.

5.1 Basic about Calibration

In modeling context, calibration is the process of using observed data to examine model

structure, verify parameters in the model, and estimate unknown parameters from relevant data. It is a great tool to help improve and fine tune models. The calibration process helps a modeler scrutinize the model structure and identify possible logical problems. In a perfect world, a System Dynamics model would precisely characterize a complex system in the external world. However, a System Dynamics model does not always reproduce the real world system perfectly. Among the reasons for model inaccuracy are logical problems in the model structure. These problems can cause misleading results or even a problematic model. Therefore, we need a way to verify and improve the model so it can have a better fit with the system it represents. Calibration provides a great method that allows us to fine tune the model structure by using observed historical data as a standard. By observing trends of model outputs and comparing them with historical data, we can identify any abnormal behavior and different trends in model outputs. With further investigation into causes of the abnormal behavior, we can identify logical problems in the model structure, data or equations.

Through the calibration process, modelers can estimate or interpolate missing data points from related data sources. During the parameterization process, data may not be available for some model parameters and initial values of stock variables. For example, the current model lacks initial values of the undiagnosed prediabetic population in the SHR. In these kinds of situations, calibration is the best tool for finding missing pieces of the puzzle. By adjusting the values of these unknown parameters in reasonable ranges, the model will produce different outputs. The calibration software compares model outputs with observed data and minimizes difference between these two data. Values of parameters that yield the best results are the best estimate for these unknown parameters.

Besides finding values for unknown parameters, calibration can help in verifying and cross checking existing data in the model. During the calibration process, we use data we obtain from other sources as the historical data. If model outputs have huge difference from the historical data, we can tell there are disagreements between the data we applied in the model and the historical data we used for the calibration. We can identify problems by tracing causes of

huge difference among model outputs and historical data.

A model calibration process involves multiple iterations of minimizing difference between historical data and model outputs and readjusting model for better outputs. As the first step, we use the modeling software to calculate gaps between observed historical data and model output and try to minimize these gaps. In this step, we create a list of model parameters that allows the modeling software to adjust freely within certain ranges. By changing values of these model parameters, the modeling software will find the best combination of parameter values, which yields a result with a minimum gap from the historical data.

After the calibration software finds the best combination, we analyze the final gap between historical data and model outputs, and estimated values of unknown model parameters. We also analyze the values of model parameters that were found by the calibration process. In the analysis step, if there is a large gap or unmatched trend between model outputs and the historical data, we try to identify any problem in the data and the model structure. Once all identified problems are fixed, we repeat the first calibration steps until we have an agreement between model outputs and historical data.

A critical part of a calibration process is measuring gaps between model outputs and historical data. We construct a calibration structure in the model to calculate the difference between model outputs and historical data automatically. Figure 5-1 illustrates the conceptual structure of the calibration process.

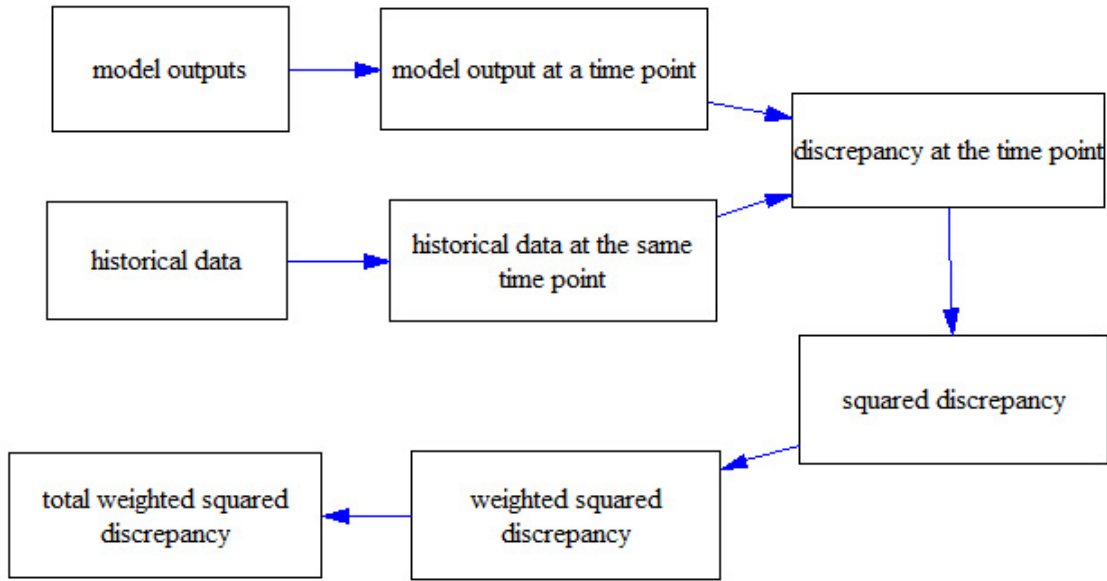


Figure 5-1. Conceptual Structure of Calibration Process

First of all, we collect historical data for model variables located in the calibration sector (“View”) of the model. Secondly, we provide the calibration sector interface to the model outputs for the same variables. After all data and equations are provided, the calibration software calculates the discrepancy between model outputs and historical data from the same time point. The discrepancy is calculated as

$$discrepancy = \left[\frac{h - m}{\left[\frac{h + m}{2} \right]} \right]^2, \quad (5.1)$$

where h is the historical datum and m is the model output. The discrepancy has desirable characters such as being dimensionless, analytic, concave, symmetric and non-negative [67]. In the second step, we weight discrepancies related to a particular different model variable at a particular point in time based on the sample size of the historic data at that point in time and its

importance. Finally, we added all weighted squared discrepancies together and define the negative sum as the final pay off.

$$\text{payoff} = -\sum \text{weighted discrepancy.} \tag{5.2}$$

Based on unknown parameters in my model and the availability of historical data, I selected five model outputs to calibrate with historical data: the total population in the SHR, the normoglycemic population in the SHR, the total mortality rate in the SHR, the prevalence rate of diabetes in the SHR and the incidence rate of diabetes in the SHR. In the next section, I will describe the calibration structure of my model.

5.2 Calibration Structure

Before I can calibrate the model, I will need to create a calibration structure that calculates gaps between model outputs and observed data. There are two main components of the calibration structure. The first component consists of the structure to calculate the discrepancy between historical data and model outputs. The second component is a list of parameters in the model whose values can be adjusted by the calibration algorithm to alter the model output. Two parts of structure rely on each other and cooperate together to calibrate the model.

5.2.1 Discrepancy Calculation

In the discrepancy calculation component of the model, I have five observed time series of historical data against which I calibrate my model. For each time series, I created a structure that is similar to the conceptual structure I explained previously and depicted in figure 5-1. After the discrepancy is calculated for all five series, I combine all weighted discrepancies as the final payoff for the calibration. To allow the reader to better appreciate the mechanisms involved in calibration, I select the calibration process for the total population in the SHR as the example to illustrate the calibration process.

Figure 5-2 illustrates the calibration structure for the total population in the SHR. The population in the SHR is separated into age, ethnic and gender groups in my model. Therefore, I collected the population data for the SHR that is separated by age, ethnic and gender groups from year 2001 to 2005, and imported that data into the calibration structure as a time series. The modeling software, Vensim, can look up a corresponding value from the time series when the time step reaches the same time stamp in the time series. The obtained historical data is stored in a variable, the *historical population by time*. The modeling software uses the value from this variable and the corresponding population from the model output to calculate the fractional discrepancy, which is the discrepancy between the two variables, measured relative to the mean values of these two variables.

$$fractional\ discrepancy = \frac{historical\ population - model\ population}{\frac{(historical\ population + model\ population)}{2}} \cdot \quad (5.3)$$

After fractional discrepancies are calculated, I further obtain squared fractional discrepancies. Squaring the discrepancies helps ensure that no negative discrepancies will cancel out positive discrepancies, and reflect that fact that a deviation of model estimate by a certain magnitude c is considered equally undesirable regardless of whether the model is under- or over-estimating the historical value by that magnitude. Squared fractional discrepancies can also ensure the total discrepancy is concave. That means a large discrepancy has larger impact on the total discrepancy than several small discrepancies even if the sum of these small discrepancy equals to the large discrepancy. Among other factors, this will tend to make the calibration prefer to spread discrepancies more “equitably” between several variables, rather than “robbing Peter to pay Paul” by eliminating discrepancies in one variable only at the cost of creating similar discrepancies in other variables.

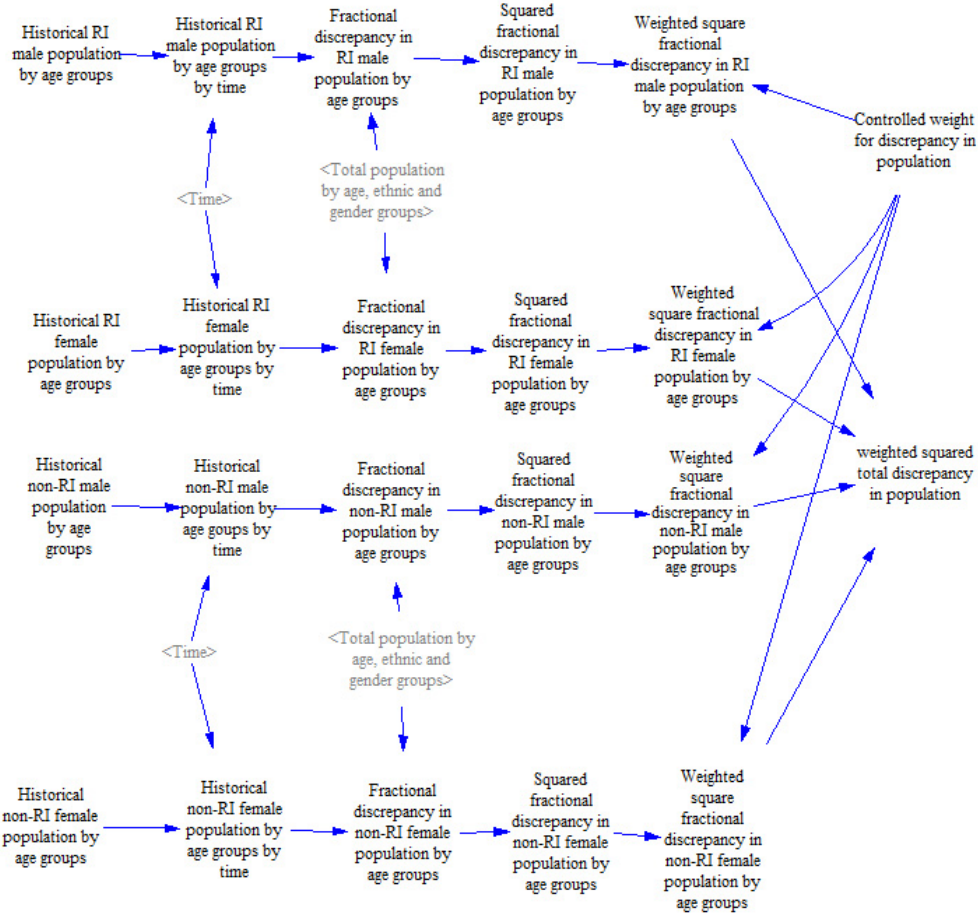


Figure 5-2. Calibration Structure for the total population in the SHR

During my first several attempts at calibration, I chose all weight to be equal. I found that some young age groups have very large (squared) fractional discrepancies that dominate the total discrepancy value. This is caused by small sample size in both historical data and model output for these age groups. A mismatch of one person count between the historic and model values with respect to these sparsely populated age groups can yield a significant fractional discrepancy. Also, these young age groups are less important to diabetes rates in the short-term than are middle age groups and elderly age groups, since the younger age groups have limited contribution to the hyperglycemic population during that time period. Therefore, in order to avoid situations such as where the squared fractional discrepancies from young age groups dominate the total discrepancy, I weighted the squared fractional discrepancies across all

calibrated outputs using weight factors. The weight factor is proportional to the reciprocal of the discrepancy function [67]. Giving a binomially distributed population, the weight factor is calculated using

$$w = \frac{1}{2} \frac{(np)^2}{(1-p)^2}, \quad (5.4)$$

where n is the population in the age group and p is the fraction of the age group in the total population.

A new issue rises to the surface after the weight factor is incorporated into the calibration structure. Huge weighted squared fractional discrepancies are calculated for middle age groups due to large weight factors, where those large weight factors are caused by the large sample sizes in these age groups. As the solution for this issue, we introduced a new parameter to limit these large weight factors. Given the factor the model has a variance, we recalculate all weight factors using

$$\bar{w} = \frac{1}{\frac{1}{w} + m}, \quad (5.5)$$

where m is the variance of the model. We make the assumption that the model has a variance of 0.1. When weight w is relatively small, the value of the new weight factor \bar{w} is closed to w ; but when the weight w is huge, the value of \bar{w} is limited by model variance m .

After limited weight factors are calculated according to (5.5), I normalized and applied normalized weight factors to calculate weighted squared fractional discrepancies rather than using non-normalized weight factors directly.

$$\text{normalized } w = \frac{\text{non-normalized } w}{\sum \text{non-normalized } w}. \quad (5.6)$$

After the weighted squared fractional discrepancy for each population group is calculated, I add all of the weighted discrepancies together as contributions of the final payoff.

The second section in the calibration structure is for calculating discrepancies in the fraction of normal weight, overweight and obese population in the youth and adult normoglycemic population. The calibration structure is similar to the calibration structure for the other time series. There are only a few differences in parameters between these two sections, such as historical data, model output and weight factors.

The historical data for this section are the weight status for the Saskatchewan population [62]. I made a simplifying assumption here that the normoglycemic population in the SHR would have the same weight distribution as the Saskatchewan population. The historical data is grouped into two age groups: the youth age group (12 – 19) and the adults age group (20 – 64). Hence, I redefined the population in the model into the same age groups corresponding to the age groups in the historical data. The time series starts from year 2001 and ends at year 2005, but it has no data available for the years 2002 and 2004.

I re-apply equation 5.4 to calculate non-normalized weight factors for discrepancies in the fraction of normal weight, overweight and obese population in youth and adult normoglycemic population. For the version of the equation 5.4 applying to this section of the model, n is the population count in each group and p is historical fraction of normal weight, overweight or obese in each group in the equation 5.4. The calculation for normalized weight factors given in formula 5.6 is used for this section as well.

The third section in my calibration structure deals with calculating discrepancies in diabetes prevalence. The calibration structure in this part is similar to the structure in other sections but uses different historical time series, model outputs and weight factors.

The historical data for diabetes prevalence rates in the SHR are calculated based on estimates for the total number of diabetic patients and the total population in the SHR. Like historical data for the total population, the historical diabetes prevalence rates are calculated for

each combination of age, gender and ethnic groups separately. This time series starts from year 2001 and end at year 2005.

Weight factors for diabetes prevalence rates are calculated by using equation 5.4, where n is the population count in the population group and p is the historical prevalence rate for the population group. I normalized these weight factors before I apply them to calculate weighted squared fractional discrepancies for diabetes prevalence.

The fourth section in the calibration structure is for calibrating with historical diabetes incidence rates. The calibration structure is the same as structures in other calibration sections, with the only differences lying in historical data, model output and weight factor.

The historical data for the diabetes incidence rate for each combination of age, ethnic and gender groups in the SHR are calculated based on the number of new diagnosed diabetic patients in the corresponding population group and the total population of that population group [61]. This time series is from year 2001 to year 2005.

The calculation of weight factors for diabetes incidence rates is different from the weight factor calculation for diabetes prevalence rates. This reflects that factor that the diabetes incidence rate is Poisson distributed with mean time occurrences λ . Weight factors for diabetes incidence rates are calculated using

$$w = \frac{1}{2} (\lambda n)^2 , \tag{5.7}$$

where λ is the historical incidence rate and n is the number of person in the population group. After non-normalized weight factors are calculated using equation 5.7, I normalize them to normalized weight factors using equation 5.6 and apply these normalized factors into the calculation of the weighted squared discrepancy in incidence rate.

Although the time series for diabetes incidence rates is from year 2001 to year 2005, the last year of data is invalid since the administrative data algorithm used to identify the cases requires two years to confirm a new diabetes case. Therefore, I conditionally set weight factors to 0 when the time reaches year 2004 and beyond.

The last section in the calibration structure is for the discrepancy in mortality. In this section, I obtain the Saskatchewan mortality rates by gender groups from year 2001 to year 2005 [73] and use them as historical mortality rates.

The calculation of non-normalized weight factors for discrepancy in mortality uses the same equation as the calculation of weight factor for discrepancy in incidence rate, where λ is the historical mortality hazard for each gender group and n is the population count in each gender group.

After all weighted squared fractional discrepancies are calculated, they are added together into the *total weighted squared fractional discrepancy*. The next step of the model calibration will alter constant parameters and repeat the discrepancy calculation to find a minimum total weighted squared fractional discrepancy.

5.2.2 List of Constant Parameters

The previous chapter mentioned many cases in which a parameter would be calibrated when I was unable to locate data for the parameter or I remained uncertain about the value of the parameter. In this section, I provide the list of constant parameters and initial values for stock variables for which I do not have sufficient data. Also, I seek to define a reasonable value range for each parameter. Vensim randomly selects a value within the given range for each parameter and calculates the *total weighted squared fractional discrepancy* resulting from a scenario in which the model is run using that set of parameter values. After exploring many possible combinations of values, Vensim will find the best combination of values for these parameters – that is, the combination of values which generates the minimum total weighted squared fractional discrepancy. Table 5-1 below contains all parameters that were calibrated in the calibration process, their value ranges, and estimated values that give the best match with historical data.

Table 5-1. Parameters in Calibration List

Parameter	Lower Boundary	Upper Boundary	Estimated Value
Init undx diabetic without complication population ethnic coefficient[Aboriginal, Other]	0.5	2.5	1.20489, 1.98039
Init undx diabetic without complication population gender coefficient[Male, Female]	0.5	2.5	1.18721, 1.10509
Init undx diabetic with early stage complication population ethnic coefficient[Aboriginal, Other]	0.01	0.1	0.0101465, 0.0999878
Init undx diabetic with early stage complication population gender coefficient[Male, Female]	0.01	0.1	0.1, 0.1
Init undx diabetic without complication population youth coefficient	0.3	1	0.808948
Init undx diabetic without complication population elderly coefficient	0.3	1	0.540365
Init undx diabetic with early stage comp population youth coefficient	0.05	0.3	0.3
Init undx diabetic with early stage comp population elderly coefficient	0.01	0.3	0.010004
Init diabetes to prediabetes coefficient[Male, Female]	0.4	2	0.4, 0.4
Init undx prediabetic population ethnic coefficient[Aboriginal, Other]	1	5	3.06172, 2.82211
Init undx prediabetic population gender coefficient[Male, Female]	1	5	2.03095, 1.66264
Avg years to develop early stage complications from undx diabetes	5	15	15
Dx diabetes progress coefficient	1	2.5	2.5
Avg years to develop diabetes from undx prediabetes	8	15	15
Dx diabetic complication progress coefficient	1	2.5	1
early stage complication diagnosis youth coefficient	0	0.5	0
early stage complication diagnosis elderly coefficient	0	1	1
early stage complication diagnosis gender coefficient[Male, Female]	0.5	1	1, 1
mortality coefficient dx diabetic without complication	0.4	1	1
mortality coefficient dx diabetic with early stage comp	0.3	2	0.3
mortality coefficient dx diabetic with late stage comp	1	4	1
mortality coefficient undx diabetic without complication	0.4	1	1
mortality coefficient undx diabetic with early stage comp	0.6	2	1.28717

5.3 Findings

Calibration is a valuable tool for estimating unknown parameters, verifying existing data and identifying problems in the model. Through the calibration process, I was able to estimate best matching values for unknown parameters listed in Table 5-1. The calibrated model gives the minimum -2503.8 weighted squared fractional discrepancy and exhibits a relatively close trend with historical data by using these best estimated values. Figure 5-3a and 5-3b below show that outputs from the model have close trends and small gaps in comparison with historical data.

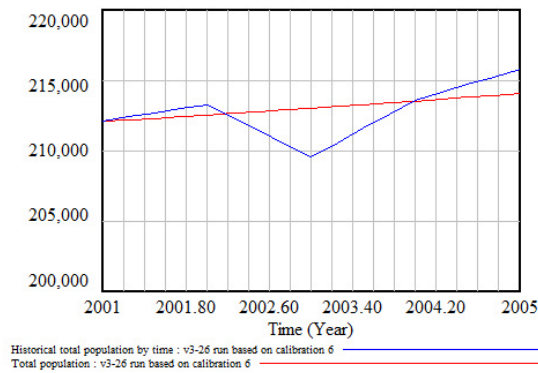


Figure 5-3a. Comparison of Total Population

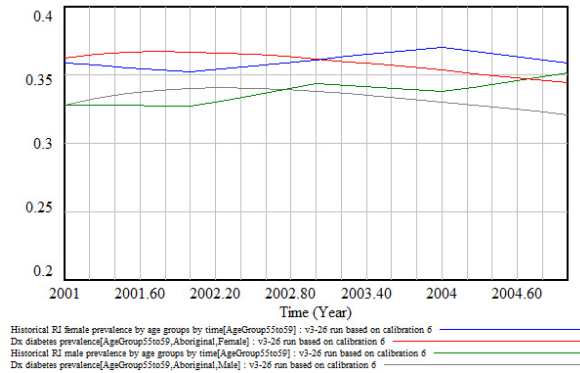


Figure 5-3b. Comparison of Diabetes Prevalence Rate for RI 55-59 Age Group

The model contains hundreds parameters and constants. We cannot always find a good match from calibration. Figure 5-4a and 5-4b show two examples of cases where the chosen parameter values assigned by calibration do not yield a good fit to historic data.

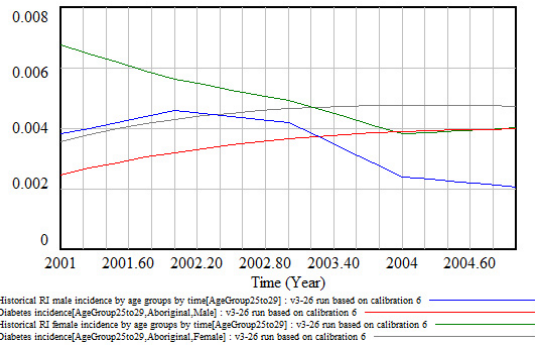


Figure 5-4a. Comparison of Diabetes Incidence Rate for RI 25-29 Age Group

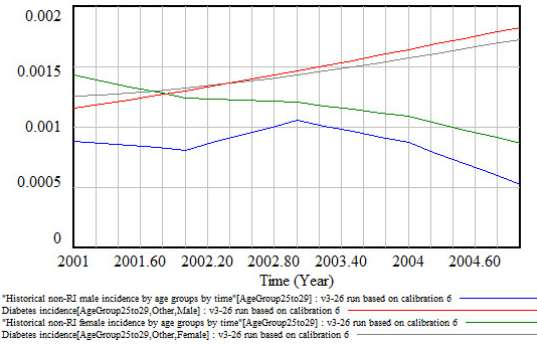


Figure 5-4b. Comparison of Diabetes Incidence Rate for non-RI 25-29 Age Group

One possible reason for poor calibration matches is that the duration of the calibration is too short. The diabetes incidence rates for the RI 25-29 age group in Figure 5-4a have large gaps and different trend at the beginning of the calibration. Although curves converge, they still do not quite match at the end of the calibration.

Another possible reason for poor calibration matches is less significance of the unmatched time series. Figure 5-4b shows very low incidence rates for non-RI 25-29 age group. Although gaps between model outputs and historical data are not large, curves are diverging during calibration. The failure of the calibration algorithm to calibrate it partly reflects the fact of the lower priority (via weight) associated with this outcome variable.

The third possible reason for poor calibration matches is that the model structure limits the possible changes of variables in the calibration. All variables in the model are related. Changes in one variable will have effects on other variables. It may not be possible to match one piece of the model to historical data without significantly diminishing the quality of another match.

Although the set of estimated values for unknown parameters generates the best match against historical data, some of these estimated values reach boundaries of given ranges. When a parameter reaches the boundary of the associated calibration range, it indicates that the calibration process may have been able to find a better match by assigning a value that is beyond

the defined range. Whether the calibration range is too tight or other issues in the model lead the estimated value to reach the boundary, such boundary values require investigation.

Several parameters in the calibration list for calculating unknown initial values of stock variables reach either the lower boundary or the upper boundary of the specified calibration range. The *Init undx diabetic with early stage complication population ethnic coefficient*, for example, reaches the lower boundary 0.01 for RI population, the upper boundary 0.1 for non-RI population. This parameter is used for calculating the initial population of undiagnosed diabetics with early stage complication from the initial population of diagnosed diabetics with early stage complication. The first thought is that the model tries to lower the initial population of undiagnosed diabetic with early stage complication for the RI group and raise the initial population of undiagnosed diabetic with early stage complication for the non-RI population. However, the lower boundary of the *Init undx diabetic with early stage complication population ethnic coefficient* is small enough to make the initial population of RI undiagnosed diabetic with early stage complication 100 times less than the initial population of RI diagnosed diabetic with early stage complication. A lower value of the *Init undx diabetic with early stage complication population ethnic coefficient* for the RI population would appear to make the number of undiagnosed RI diabetic with early stage complication unrealistically small. In addition, I manually adjusted the value of the *Init undx diabetic with early stage complication population ethnic coefficient* for the RI population to an unrealistically low value, but it did not reduce the total weighted squared discrepancy significantly. I also tried to adjust the *Init undx diabetic with early stage complication population ethnic coefficient* to values greater than the upper boundary, but there was no significant improvement in the total weighted squared discrepancy. Similarly, I tried to recalibrate the model by giving wider ranges to these parameters, but I still did not see any significant improvement. A possible explanation is that these parameters are for calculation of initial values of stock variables. Initial values are only used for starting the simulation. In some circumstances, changes in initial values of stock parameters would fade out through the simulation process and will not have large impact on the final result.

Beside parameters for calculating unknown initial values, some unknown constant parameters in the calibration list reach the boundary as well. For instance, the *mortality coefficient undx diabetic without complication* is one of the unknown constant parameters that reach the upper boundary. However, there is no space allowing me to loosen the boundary. The *mortality coefficient undx diabetic without complication* is for calculating the mortality of undiagnosed diabetic without complication population based on the average mortality of diabetic population, which includes the diabetic with early stage complication population and the diabetic with late stage complication population. By its definition, the diabetic without complication population has the lowest risk compared to the diabetic with early stage complication and the diabetic with late stage complication population. Therefore, the mortality of undiagnosed diabetic without complication population should not be higher than the average mortality of diabetic population and the *mortality coefficient undx diabetic without complication* should not be higher than 1. Similarly, the *mortality coefficient dx diabetic with late stage comp* is for calculating the *mortality of dx diabetic with late stage complication* from the *all other causes mortality of dx diabetic with early stage macrovascular complication population*. It should not be less than 1 since diabetic with late stage complication population has much higher risk than diabetic with early stage complication population.

It is clear that the model has some issues causing values of unknown parameters reach boundaries. Unfortunately, I do not have enough time to do further investigation within the scope of the thesis.

Calibration also is a useful tool for verifying and cross checking data in the model from related historical data. The data used in the model should produce the results similar to historical data from a different data source, especially at the beginning of a simulation. For example, the sum of each population groups in the model should match the covered population in the SHR in year 2001 at the beginning of a simulation. If data from different sources has a disagreement, then either model data or historical data has problem. At the beginning of my calibration process, there was a difference between the initial total population in the model and the total covered

population from the SHR's reports. After a quick investigation, I found there was an input error in the historical data, which could have caused a much bigger problem later.

Besides verifying data in the model, calibration can be used to examine model structure as well. I was able to identify some bugs in my model structure through the calibration process, such as missing an input population subgroup when accumulating individual population subgroups to an aggregate population group.

5.4 Summary

Calibration is a valuable tool for estimating values for unknown parameters, verifying data in the model and examining model structure. Through the calibration process, we made the model more robust, reliable, and eliminated model formulation problems.

In Chapter 5, I explained the procedure of calibration in the modeling world. First of all, I briefly explained the basic calibration structure and procedure by going through a conceptual calibration structure. The basic calibration procedure includes several iterations of calculating discrepancies between the model outputs and historical data based on possible model parameter values and adjusting such parameters so as to minimize such discrepancies, while remaining inside specified ranges for the adjusted parameters. I also explained some basic components in a calibration structure; such as model data, historical data, discrepancy and payoff.

After explaining some basic facts about model calibration, I provide a detailed explanation of my calibration structure. There are total five time series in my calibration structure: the total population count in the SHR, the weight status for the Saskatchewan population, the total mortality of the Saskatchewan population, the diabetes prevalence rate in the SHR and the diabetes incidence rate in the SHR. Calibration structures for these five time series are very similar. Therefore, I selected the calibration structure for the total population in the SHR as an example to explain the discrepancy calculation. I also explained the weight calculation for different time series.

Finally I discussed several important findings from the calibration process. It is clear there are some issues in the model when calibrated parameters reach boundaries. These issues will be added into my future work list.

CHAPTER 6

RESULTS

As my thesis title suggests, the ultimate goal of my study is to create a simulation model for the burden of Type 2 Diabetes in the Saskatoon Health Region. After the calibration process, major structural defects in the model are corrected and missing parameters are plugged into the model with the best estimated values. Robustness and integrity of the model are improved to an acceptable level. The model is able to reproduce the historical burden of diabetes in the SHR with an adequate degree of fidelity. The model now can be used to project the trend of diabetes burden in the near future; longer-term projection is possible, but results are contingent upon assumptions regarding exogenous factors (e.g. assumptions regarding changes in the incidence of overweight and obesity, migration, changes in diagnostic technologies and treatments for pre-diabetes, diabetes and complications). It also can be used as an assistant tool to help decision makers understand the basic causes of diabetes burden and test potential intervention policies.

The burden imposed by Type 2 diabetes includes many components such as the diabetes prevalence, the diabetes incidence rate, the diabetes-related costs for the health care system, the diabetes-related costs for individual patient, and the quality of life.

In this chapter, I am going to focus on the diabetes prevalence and the diabetes incidence rate as the diabetes burden. I will illustrate some simulation results as important indicators, such as diabetes prevalence and diabetes incidence. I use the model to simulate the evolution of the diabetes burden in the Saskatoon Health Region in the next 100 years from year 2001. The simulation results will show the dynamics of diabetes burden in the SHR and create a broad picture of the diabetes burden in the future.

6.1 Simulation Results

After the model is calibrated, I ran the model to simulate the diabetes burden from year 2001 to year 2101 based on current conditions. The simulation results are the projections of the

diabetes burden without any intervention, and assuming current levels of exogenous factors. These results can provide a good view on the trend of diabetes burden.

Figure 6-1 illustrates the trajectory of the total population in the SHR. The projection of the total population slowly increases during the first 20 years of the simulation period. After the total population reaches its peak level around the year 2025, it starts to decrease slowly.

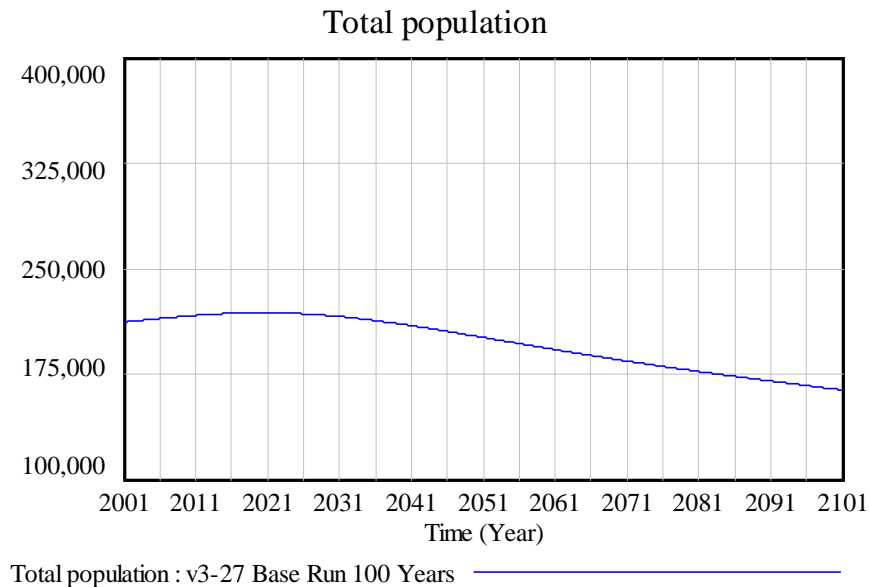


Figure 6-1. Total Population

The diabetic population in the SHR is the most important indicator of diabetes burden. Figure 6-2a shows the simulation result of the total diabetic population from year 2001 to year 2101. The total diabetic population increases in the first half simulation period. It reaches the peak level between year 2046 and year 2056, and slowly decreases afterwards. Figure 6-2b illustrates the diabetic populations in different ethnic and gender population groups. Most of the diabetic population is non-Aboriginal due to the large population base. The Aboriginal female diabetic population is slightly greater than the Aboriginal male diabetic population during the entire 100-year simulation period. The non-Aboriginal female diabetic population is a little less than male at the beginning of the simulation, but it quickly rises to exceed the number of male non-Aboriginal diabetic population around the year 2015.

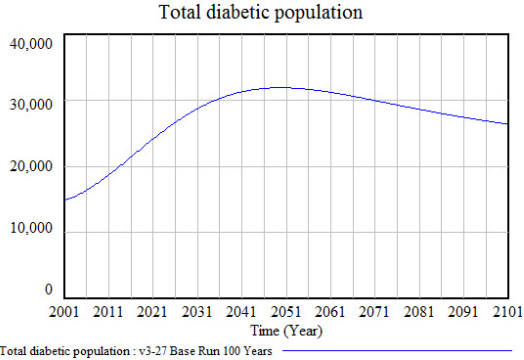


Figure 6-2a. Total Diabetic Population

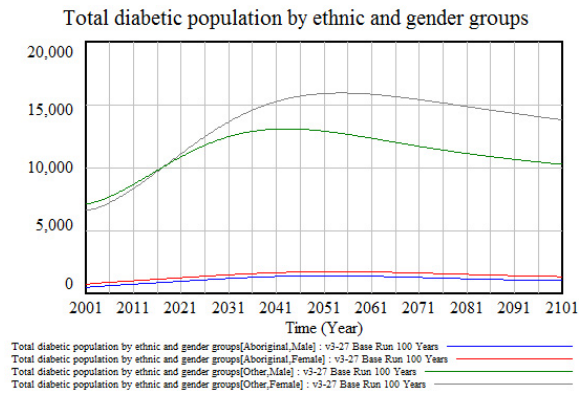


Figure 6-2b. Total Diabetic Population by Ethnic and Gender Groups

The dynamics in the size of the total diabetic population is influenced by many factors in the model. These factors cause the observed behavior in the size of the total diabetic population. The change in the obese population is one of the leading causes of this trend. As is widely known, obesity is the most important risk factor of developing type 2 diabetes. An increase in the obese population will lead to growth in the prediabetic population and further spur an increase in the diabetic population. The simulation results from my model show that the obese population increases immediately and reaches a peak level between year 2021 and year 2026. The increase in the obese population leads the increase in the prediabetic population.

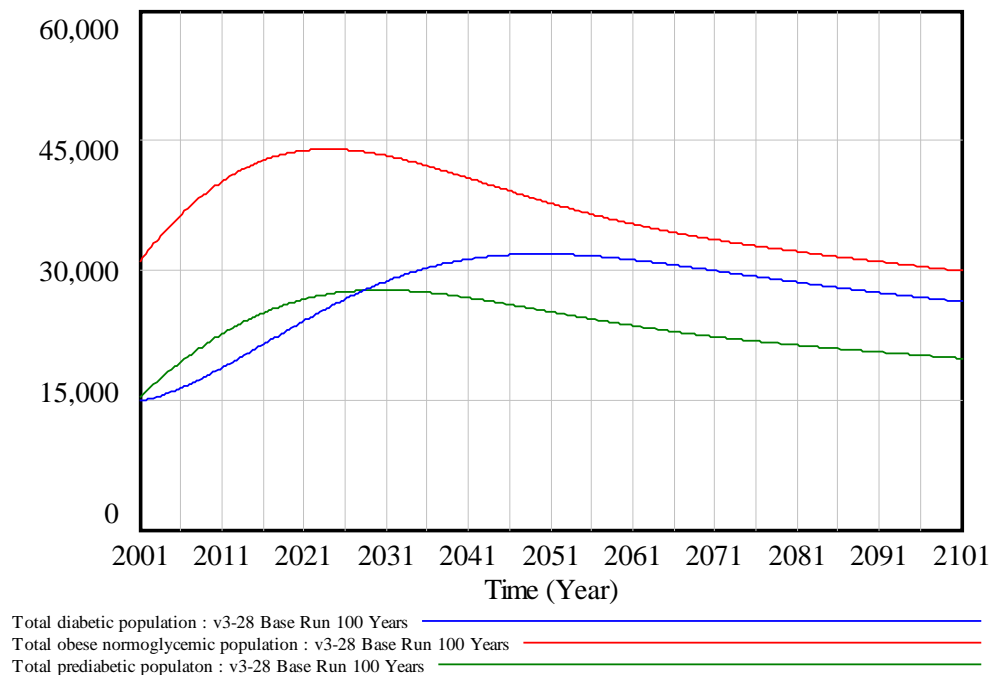


Figure 6-3. Comparison of Total Obese normoglycemic, Prediabetic and Diabetic Population

Figure 6-3 shows that the prediabetic population increases with a slightly slower speed and slight delay from, but with a little longer term than the obese population. The prediabetic population reaches its peak level between the year 2026 and the year 2031. The diabetic population also increases with the obese population but with a slower speed because of the long time delays involved and because not every obese person will develop diabetes. The increase in the diabetic population also has a longer period than the increase in the obese population since it will take years to develop diabetes. Figure 6-2 shows that the diabetic population reaches its peak level between the year 2046 and the year 2051.

The size of the diabetic population indicates an important component of the absolute burden of diabetes, but it does not reflect the relative level of burden within some population groups. The prevalence of diabetes is an appropriate indicator for highlighting the relative level of the diabetes burden in population groups. Although the number of RI diabetic patients is much less than the number of non-RI diabetic patients, the prevalence of diabetes in the RI population is

not less than the prevalence of diabetes in the non-RI population. Figure 6-4 shows that the prevalence of diabetes in RI female population is higher than the prevalence in the non-RI female population until the year 2071. The prevalence in the RI male population is very close to the prevalence in the non-RI male population. Figure 6-4 also shows that the prevalence in the female populations is higher than in the male population for both RI and non-RI groups for the most of time simulation timeframe. However, Figure 6-4 does not itself show an important contributing factor affecting the results shown: The age structure of the underlying population. We discuss this next.

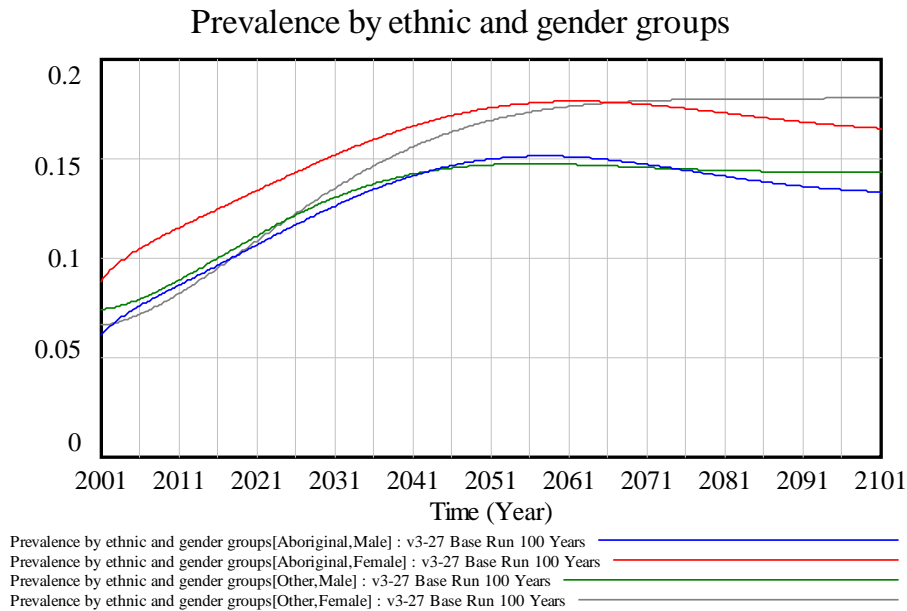


Figure 6-4. Diabetes Prevalence by Ethnic and Gender Groups

The diabetes prevalence among the non-RI populations keeps a steady state after it reaches its peak value. However, the diabetes prevalence among the RI population starts to decrease after reaches the peak value. One major reason is the Aboriginal population count decreases after the year 2040. Due to insufficient data for the birth rate of the Aboriginal population, I applied the birth rate of the general population to the Aboriginal population in the model. The decreasing in the Aboriginal population causes the decreasing in the Aboriginal diabetic population and further causes the decreasing in the diabetes prevalence among the Aboriginal population.

Another major reason is the age structure of the Aboriginal population. The prevalence and the incidence rates of population groups in the model are not age standardized. Since a large percentage of the Aboriginal population are young, the prevalence of diabetes is low for the Aboriginal population. However, the low prevalence of diabetes does not mean they are healthier than others. The youth are still in high risk of developing diabetes.

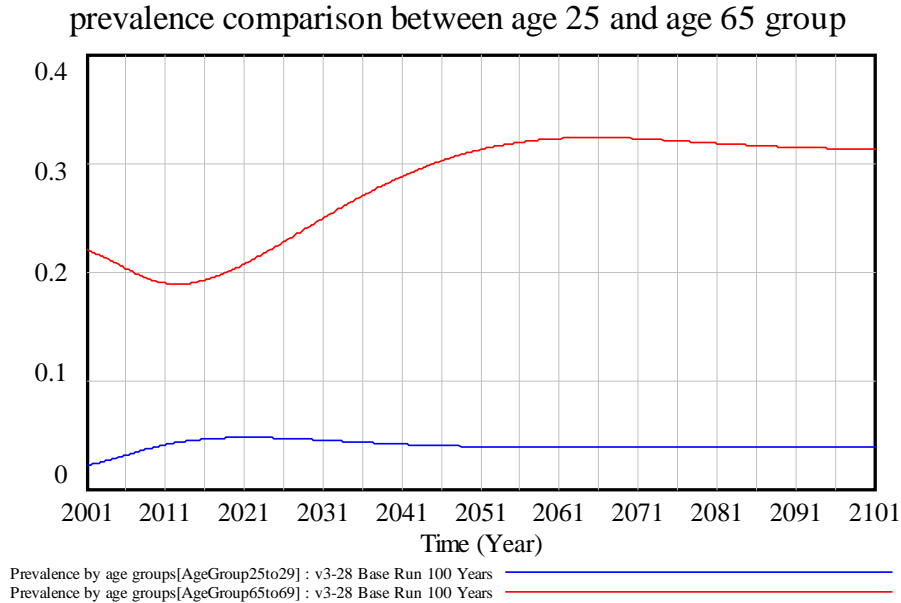


Figure 6-5. Comparison between Age 25 and Age 65 Population Groups

The simulation results also indicate that older age groups have higher diabetes prevalence than younger age groups. It is well known the risk of Type 2 diabetes is highly associated with age. The simulation results clearly show the relationship between age and diabetes. Figure 6-5 illustrates that the diabetes prevalence of the *age group 65 to 69* is much higher than for *age group 25 to 29*.

In addition to the diabetic population and the diabetes prevalence discussed above, the number of incident cases per year is another important factor to indicate diabetes burden. It reflects the acceleration of the diabetes burden. A rise in incidence cases leads to a faster increase in the diabetic population and in other components of the diabetes burden as well. Figure 6-6a

illustrates the trend of diabetes incidence over the next 100 years. The total incidence case drops in the first 5-year period, which may be due to a drop in the total population and that the incorrect initial values which are not consistent with the estimated transition rates. After the first 5-year period, the impact of the incorrect initial values fades out and the rate of diabetes incidence starts rising. The number of incident cases per year reaches the peak value - 1106 person per year - in year 2031, and then start dropping slowly afterwards due to the decreasing in the population at the risk.

As Figure 6-6b shows, the number of diabetes incident cases per year in the Aboriginal population basically exhibits the same trend as the total number of incident cases. However, the number of incident cases in the Aboriginal population has a longer increase time period. It reaches its peak value around year 2041 compared to year 2031 for the total number of incident cases. After it reaches the peak value, the annual number of incident cases rapidly decrease. Similar to the prevalence of diabetes for the Aboriginal population, the decrease in the annual number of incident cases for the Aboriginal population is caused by the decrease in the potential population and the age structure.

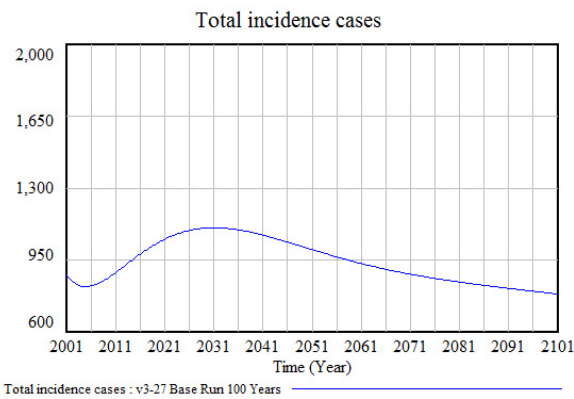


Figure 6-6a. Total Incident Cases

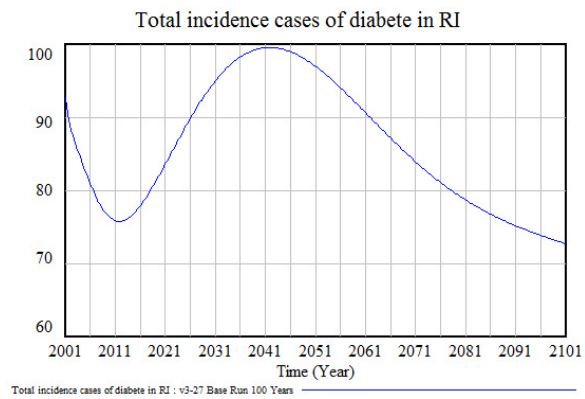


Figure 6-6b. Total Incident Cases in RI Population

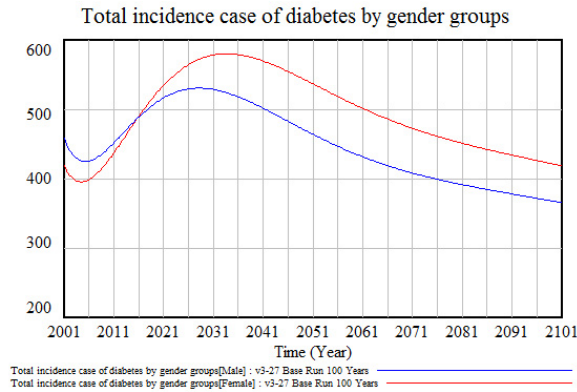


Figure 6-6c. Total Incident Cases by Gender Groups

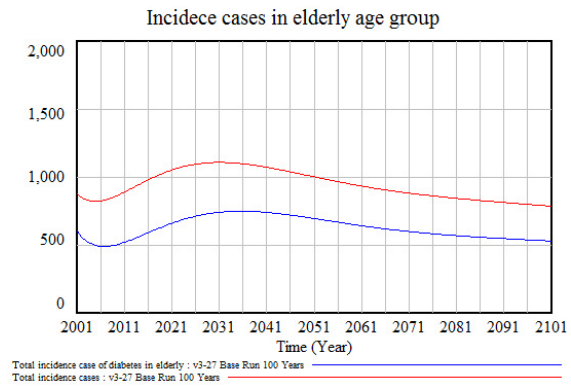


Figure 6-6d. Total Incident Cases in Elderly Age Group

Figure 6-6c illustrates that the number of annual incident cases in the female population increases more rapidly than the number of annual incident cases in the male population. The model suggests that the absolute number of new cases in the female population per year will exceed the number of annual new cases in the male population around year 2016. The number of annual incident cases in the female population raises until year 2036, but the number of annual incident cases in the male population rises until 2026. These results suggest that diabetes may increase faster in the female population than in the male population. The number of annual incident cases in both male and female population start to decrease after they reach their peak values due to the decrease in the potential population.

Similar to the diabetes prevalence, the annual diabetes incidence for the elderly population is much higher than the annual incidence for the youth population. Figure 6-6d shows that the number of new annual cases of diabetes from the elderly population (age 50 and plus) forms about $\frac{3}{4}$ of the total number of new annual cases of diabetes.

The simulation results appear to be relatively reasonable projections of the diabetes burden in the SHR in the medium-term future. The results suggest that the diabetes prevalence and the annual incident of new cases will rise during the first half simulation period. The annual incident of new cases, however, will decrease during the second half simulation period due to the decrease of the potential population. The decrease in the annual incident of new cases of diabetes will slow

down the acceleration of diabetes prevalence. The decrease of potential diabetic population and the young age structure will finally lead a small decrease in the diabetes prevalence for the Aboriginal population.

Through the analysis, we can point out the major causes of diabetes burden and plan targeted interventions to reduce diabetes burden. For example, the simulation results show the diabetes prevalence and incidence are high among the female population. One possible intervention could be having physical activity or healthy eating programs specifically targeted on obese or overweight females to reduce the rate of new cases of diabetes in the female population. However, the simulation results are scenario projections. They have limitations due to the availability of data and simplification of the model structure. In the next section, I will explain the limitations of the model.

6.2 Limitations

The simulation model is a very useful tool to help us understand the diabetes burden in the SHR and to predict the trend of the burden. However, it is not a magic crystal ball that allows us see the future. The model has some important limitations. Hence we must treat the simulation results carefully in order to avoid misleading analysis results and improper interventions.

Figure 6-6a shows a decrease in the total number of new cases of diabetes in the first 5-year simulation period. It is clear the rate of incident cases is not in an equilibrium state at the beginning of the simulation. One possible reason is incorrect initial values such as the initial diabetic population, the initial mortality rate or the initial diagnosis rate. The incorrect initial values are out of balance with the estimated transition rates; and the inconsistency leads to an oscillation during the beginning of the simulation. After the effect of initial values faded out, the diabetes incidence raises.

Some of the initial values for the model are carefully chosen from historical data and related research. Some of the initial values are the best estimates from the calibration process. It is possible the estimated initial values are at variance with the true underlying values, but they are reasonable estimates based on available data. Moreover, uncertainties in model parameters may

not cause the same uncertainties in the model outputs or may only have limited impacts on the model outputs. I examined impacts from uncertainties in several model parameters in chapter 7. Even if the uncertainties have large impacts on the model result, but they may not exert a large change on relative desirability between different interventions.

The model results are not age standardized. Hence, the age structures of population groups have impacts on the results that cross age groups, such as the prevalence and the incidence rates. This is one of the reasons that cause the prevalence and the incidence rates to drop for the Aboriginal population during the second half of the simulation period.

The model also does not consider the effect from migration of the population. The population in the city of Saskatoon is growing. A large part of the growth is the migration from other cities, provinces and countries. I made a simplifying assumption in my model that the population is only affected by the birth rate and mortality rate, but experience no net migration. This simplification could lead less population in the simulation results than it should be if the population in the city of Saskatoon keep grows. This may lead to a smaller size of diabetic population in the simulation results. However, the trend of population migration is difficult to predict since it depends on many factors. For many years, Saskatoon experienced a net outmigration of population. The prediction of population migration does not fall within the scope of this thesis. I will leave the population migration section out of my study and the addition of a population migration section can be a possible topic for farther study.

The model is not to be intended to forecast the exact diabetes situation in the future. There are many factors that our model does not consider. We made simplifying assumptions about these factors. The result from the model is one possible projection conditional on certain assumptions.

6.3 Summary

The goal of my study is to build a model simulating the dynamics of diabetes in the SHR and to use the simulation results to analyze the diabetes burden in the SHR. In the previous

chapters, I explained the construction of my model. In this chapter, I explained the findings from the simulation.

The simulation results suggest that the diabetes burden will increase in the next 30 to 40 years. Both the diabetes prevalence and new diagnosis incidence cases will go up for all ethnic and gender groups. The number of diabetes new diagnosed incidence for the general population in the SHR increases and will reach a peak value around the year 2031. The increase of the number of new diabetes cases in the Aboriginal population has a longer time period and it will reach the peak value around the year 2041. After the number of diabetes new diagnosed cases reaches the equilibrium, it will decrease slowly. The decrease in the number of annual incident of new cases slows down the acceleration in the diabetes prevalence. The prevalence of diabetes continuously increases until around the year 2051. The increases are especially notable in the Aboriginal population and female population. The Aboriginal female population has the highest diabetes prevalence among all ethnic and gender groups.

The simulation results suggest that, absent aggressive intervention, the diabetes prevalence is likely to continuously increase and will not slow down in the near future. We will need to think of feasible interventions to slow down the rate of increase or even reduce the diabetes burden. In the next chapter, I will test the sensitivity of model parameters that are related to the simulation results and examine some possible interventions based on the observed parameters' sensitivity.

CHAPTER 7

SENSITIVITY ANALYSIS AND INTERVENTIONS

The simulation results suggest that the diabetes burdens, especially the diabetes prevalence and the incidence rate in the SHR will keep increasing in the near future. It is important to find solutions to slow the increase or even lower the diabetes prevalence and the incidence rate. Before we can start our investigation, we need to know which model parameters have a large impact and which only have small impacts on the diabetes burdens. If all other things are equal, we would anticipate that intervention policies based on changes on the parameters which have large impact on the simulation results would have a larger effects on the diabetes burdens. In this chapter, we will investigate which parameters have large impacts on the model results through sensitivity analysis (SA). The sensitivity analysis of model parameters will show the importance of the parameters to the model outputs. I will examine the sensitivity of the several parameters in the model, such as the prediabetes diagnosis rate, the diabetes diagnosis rate, the overweight incidence rate, etc. By altering the values of the chosen parameters to 80%, 85%, 90%, 95%, 105%, 110%, 115% and 120% of the original values, we can observe the changes on the model outputs and determine the levels of impacts from these altered parameters.

After the sensitivity analysis, I will examine several interventions based on our observations. By comparing the results from different interventions side by side, decision makers more easily find the impacts from different interventions and adapt them to a feasible intervention policy for the SHR. The results from sensitivity analysis are also useful to point out directions of future research.

7.1 Sensitivity Analysis

In the sensitivity analysis, I examined the sensitivity of selected variables in the model. The simulation timeframe begins in year 2001 and extends for 100 years. These test variables undergoing sensitivity analysis are systemically selected because of their impacts on the flow rates in the model. They have the potential of changing simulation results all the way through entire simulation period.

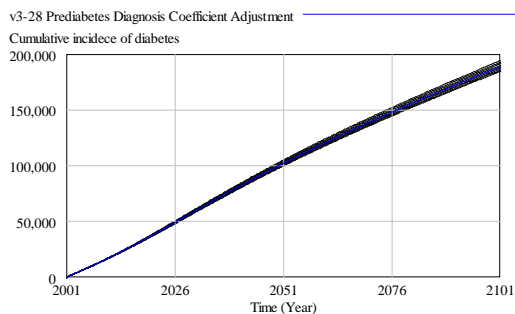
The test variables are selected from 4 general categories: the hyperglycemia diagnosis rates, the progress rates, the mortality rates, and the birth rate. The selected hyperglycemia diagnosis rates are the *prediabetes diagnosis rate* and the *diabetes diagnosis rate*. The selected progress rates include the *overweight incidence rate*, the

obesity incidence rate, the developing prediabetes from obese incidence rate, average years to develop diabetes from undiagnosed prediabetes, average years to develop diabetes from diagnosed prediabetes, average years to develop early stage complication from undiagnosed diabetes, average years to develop early stage complication from diagnosed diabetes and the prediabetes recovery rate. The selected mortality rates include the *mortality rate of the diagnosed prediabetic population, the mortality rate of the diagnosed diabetic without complication population, the mortality rate for the diagnosed diabetic with early stage complication population, and the mortality rate for the diagnosed diabetic with late stage complication population.* The selected birth rate is the *SHR birth rate* for the Aboriginal population.

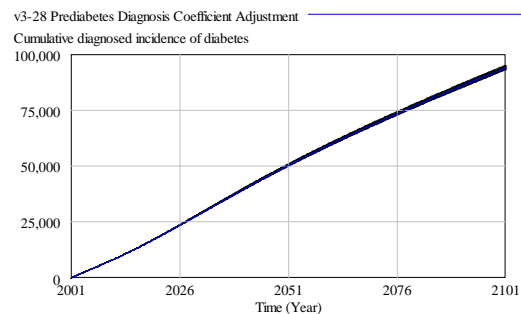
I also added several aggregative results variables, which summarize values cross the population, into the model to help the reader observe and compare the changes during the sensitivity analysis. These result variables are the *cumulative incidence of diabetes, the cumulative diagnosed incidence of diabetes, the cumulative number of diabetic, the cumulative number of diagnosed diabetic and the cumulative death of diabetic.* Besides cumulative result variables, I also employed two non-cumulative result variables, the *total prevalence of diagnosed diabetes and the total diabetes incidence,* to show the system responses from the changes of the test variables. These result variables will be plotted into graphs to illustrate the changes.

7.1.1 Single-variable Sensitivity Analysis

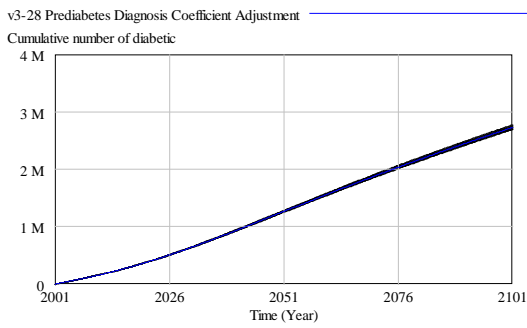
I start my sensitivity analysis by only altering one test variable each time and observe the changes in the result variables. This process helps us answer the question “which variable has a large impact on the simulation results”. It also provides a solid foundation for the next step sensitivity analysis with multiple variables on the selection and combination of modifications to the test variables.



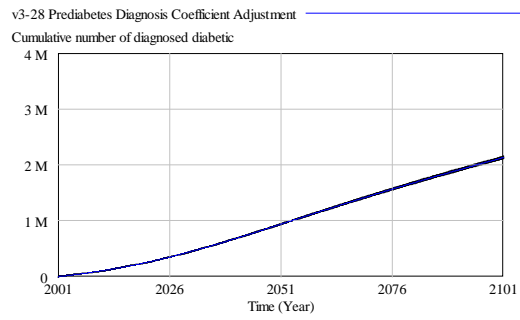
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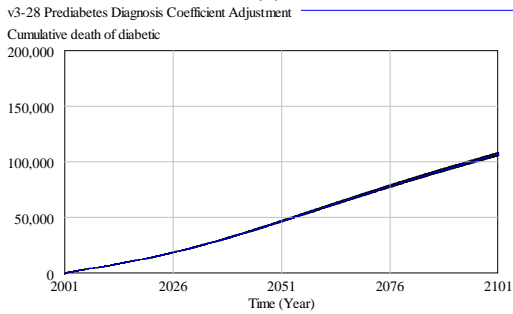
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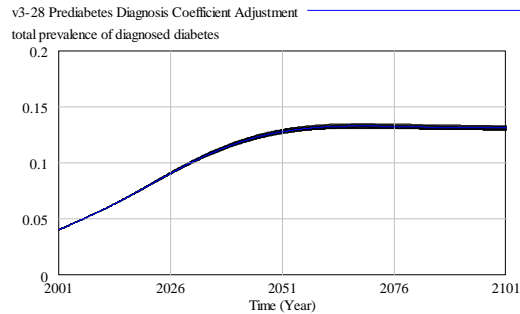
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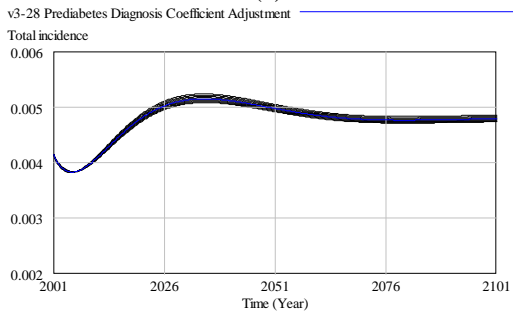
(d)



(e)



(f)



(g)

Figure 7-1. Sensitivity Results for Prediabetes Diagnosis Rate

Figure 7-1 shows the sensitivity results for the *prediabetes diagnosis rate*. Figure 7-1a suggests that the *cumulative incidence of diabetes* is sensitive to the changes in the *prediabetes diagnosis rate*. The changes in the *prediabetes diagnosis rate* affect the number of diagnosed prediabetic population and further affect both the undiagnosed and diagnosed diabetes population. Figure 7-1b and 7-1d show the levels of impacts from the changes in the *prediabetes diagnosis rate* are reduced for the *cumulative diagnosed incidence of diabetes* and the *cumulative number of diagnosed diabetic* since a component of diagnosed prediabetic will develop diabetes without being diagnosed. The impacts are also delayed for the *cumulative number of diabetic* as the Figure 7-1c shows since it will take years to develop diabetes from prediabetes. The impacts are further reduced and delayed for the *cumulative death of diabetes*. However, the *total*

prevalence of diagnosed diabetes and the total incidence are relatively sensitive to the changes in the prediabetes diagnosis rate.

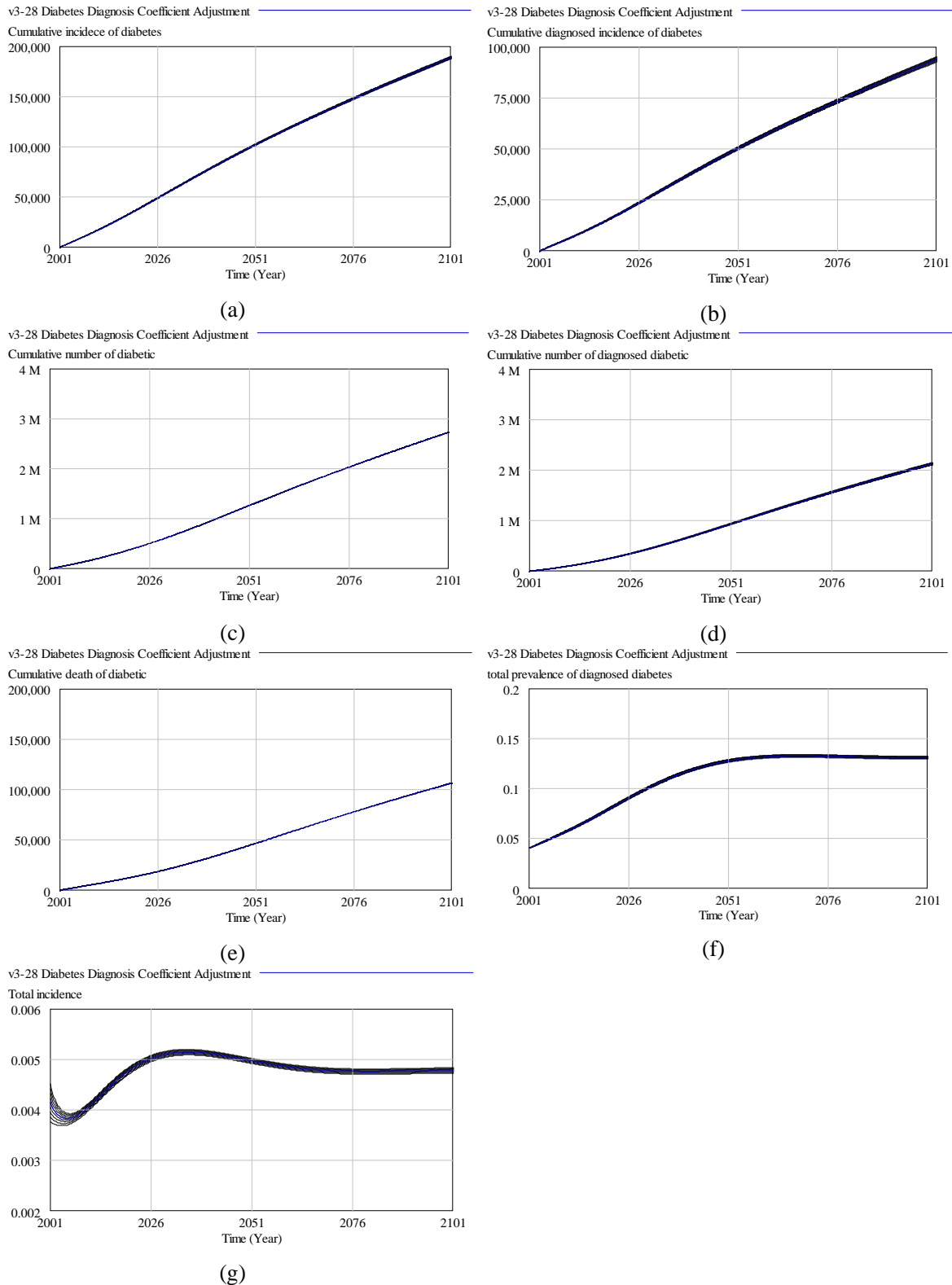
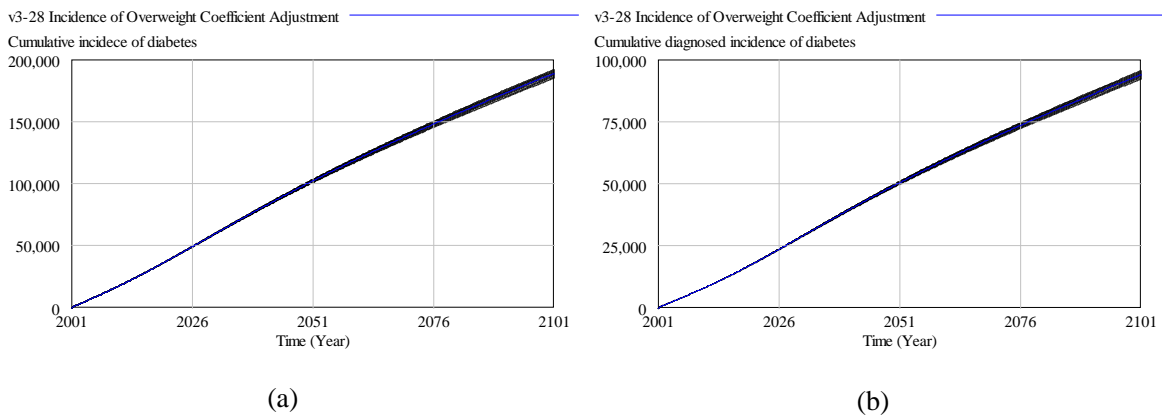


Figure 7-2. Sensitivity Results for Diabetes Diagnosis Rate

Figure 7-2 shows the sensitivity results for the *diabetes diagnosis rate*. The *diabetes diagnosis rate* controls the population flow speed from the undiagnosed diabetic population to the diagnosed diabetic population. This is associated with only one of several diabetes diagnosis paths that are included in the model to calculate the *cumulative incidence of diabetes*. Figure 7-2a shows the *cumulative incidence of diabetes* responses but is not too sensitive to the changes in the *diabetes diagnosis rate*. Figure 7-2b shows the changes in the diabetes diagnosis rate have slightly heavier impacts on the *cumulative diagnosed incidence of diabetes* than on the *cumulative incidence of diabetes*.

Diabetes diagnosis from the undiagnosed diabetic population is a diagnosis flow and it does not affect the timing diabetes onset. Hence, the changes in the *diabetes diagnosis rate* visually have no impact on the *cumulative number of diabetic* as shown in Figure 7-2c. However, the changes in the *diabetes diagnosis rate* affect the flow rate of the undiagnosed diabetic population becoming diagnosed and further change the *cumulative number of diagnosed diabetic* as shown in Figure 7-2d.

The diagnosed diabetic population has very similar mortality as the undiagnosed diabetic population. The changes in the diabetes diagnosis rate visually have no impacts on the *cumulative death of diabetic* as shown in Figure 7-2e. Graph 7-2g shows that the *total incidence* is sensitive to the change in the *diabetes diagnosis rate*. Any change in the *diabetes diagnosis rate* will be reflected in the *total incidence* immediately. Similarly, the impacts are reflected to the *total prevalence* of diagnosed diabetes immediately, but the levels of impacts are diluted by the total population as shown in Figure 7-2f and accumulate only over time.



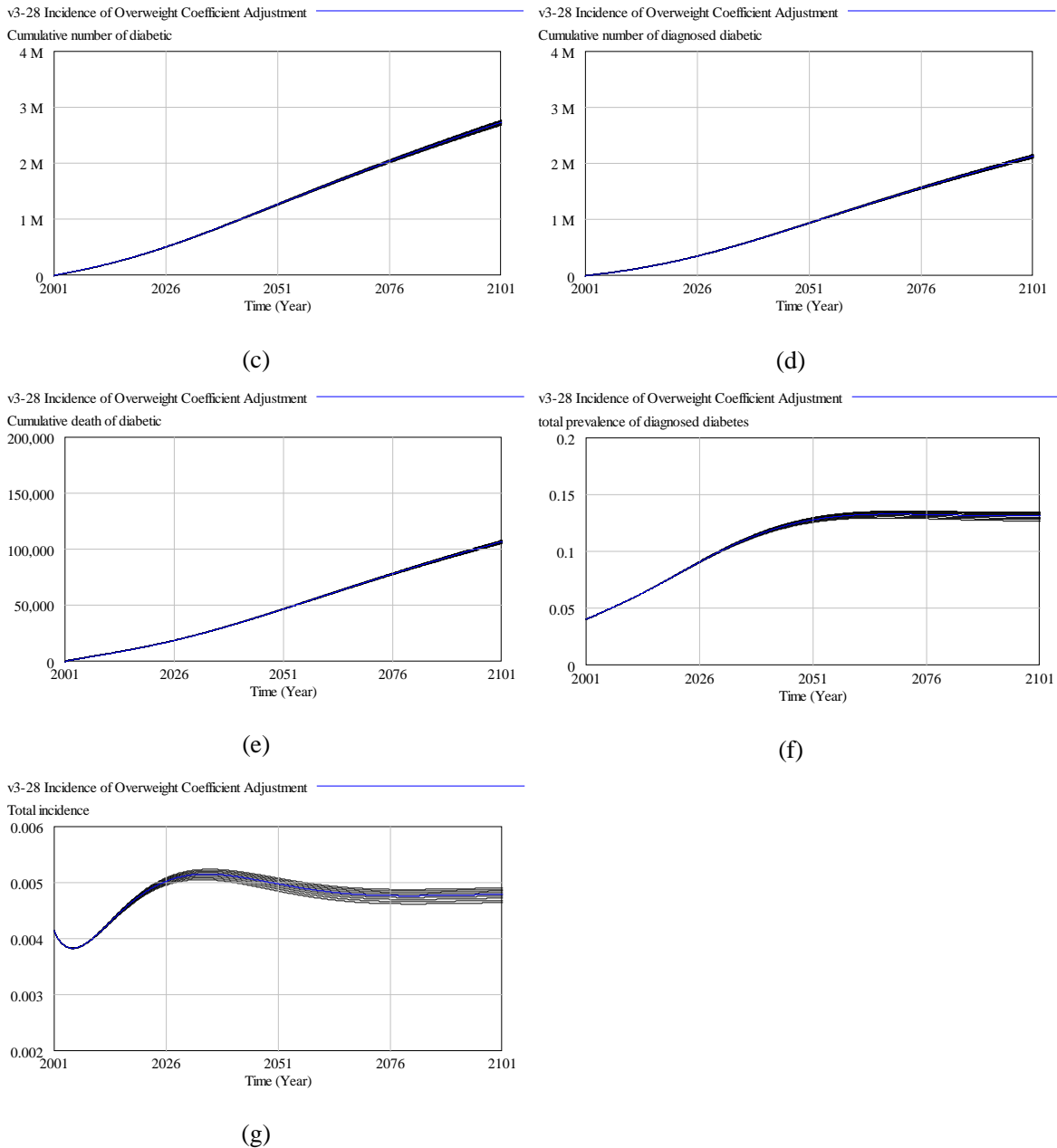


Figure 7-3. Sensitivity Results for Overweight Incidence Rate

Figure 7-3 shows the sensitivity results for the *overweight incidence rate*. This sensitivity analysis alters the incidence rate of becoming overweight from the normal weight normoglycemic population. The figures from 7-3a to 7-3e show that the changes in the *overweight incidence rate* impact the results variables in the long run. The impact has been delayed since it will take relatively long time to develop diabetes from the overweight normoglycemic population. Also, the changes in the *overweight incidence rate* have a relatively large impact on the *total prevalence of diagnosed diabetes* and on the *total incidence* in the long run since they impact on the diabetic population.

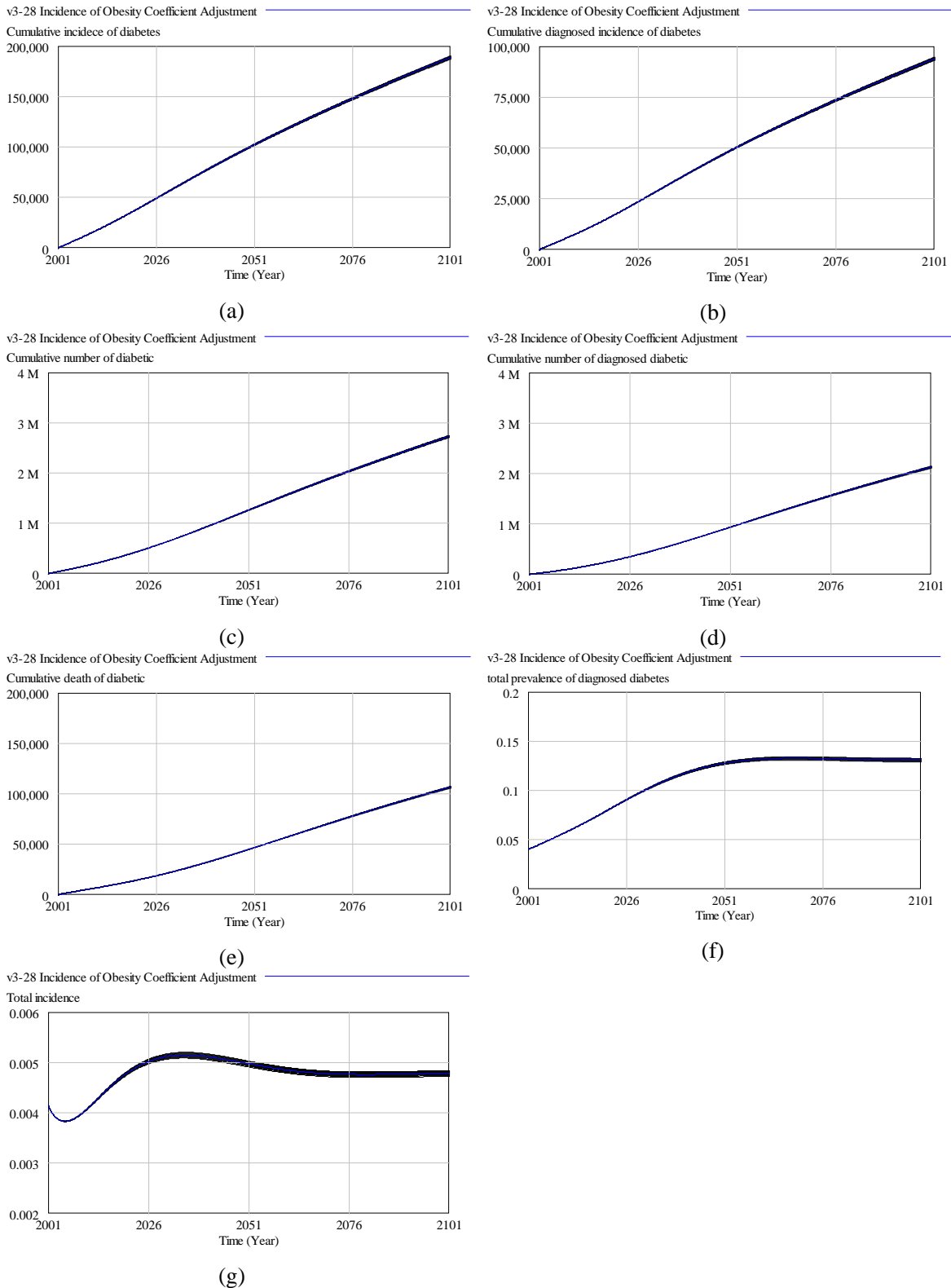
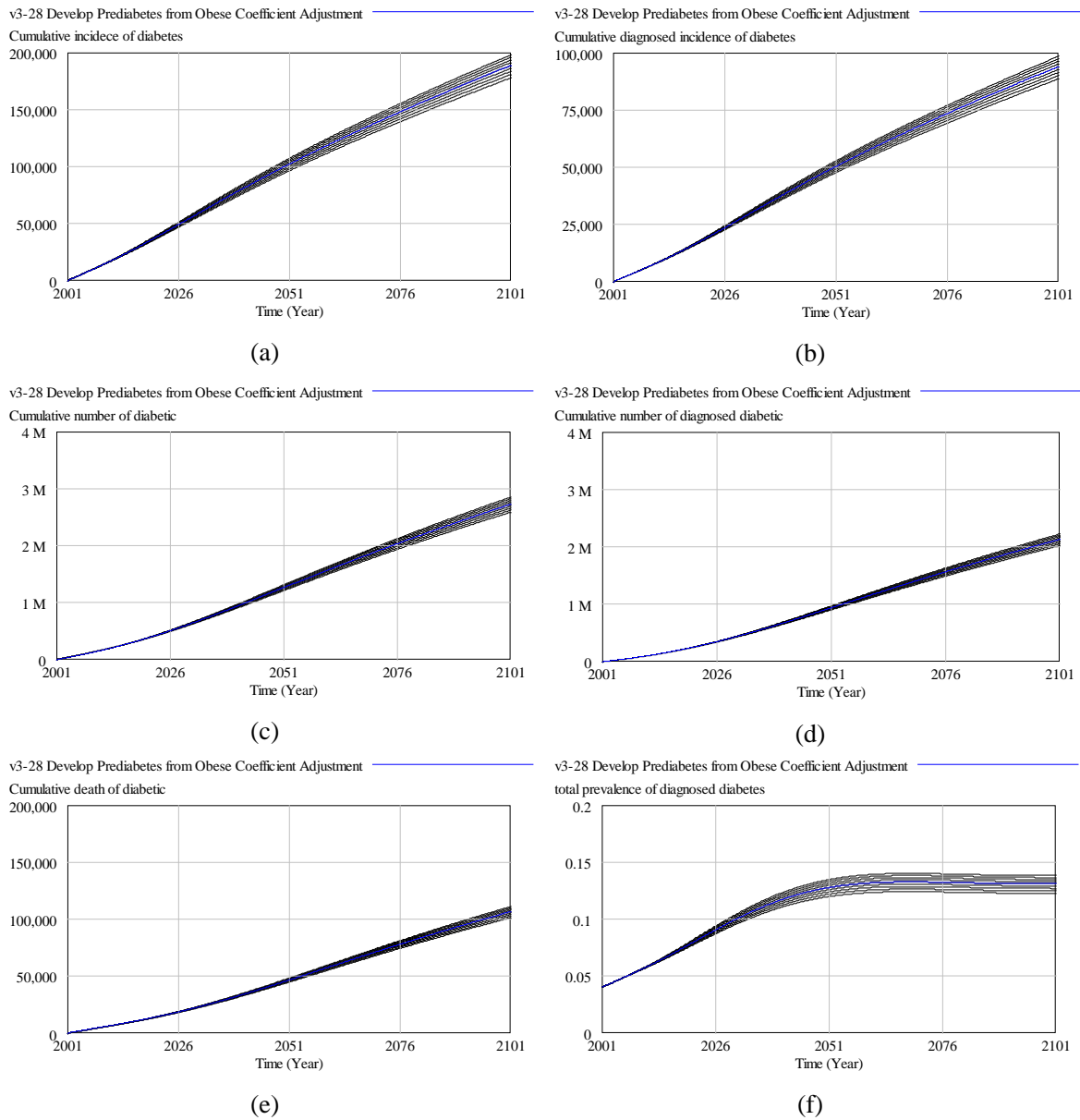
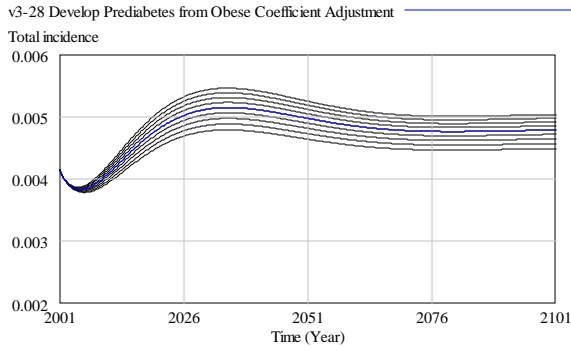


Figure 7-4. Sensitivity Results for Obesity Incidence Rate

Similar to the *overweight incidence rate*, the changes in the *obesity incidence rate* have a long run impact on the cumulative diabetic result variables, the *total prevalence of*

diagnosed diabetes and the *total incidence*. Figure 7-4 illustrates the long run impacts from the changes in the obesity incidence. Compared to the impact from the changes in the *overweight incidence rate*, the impact from changes in the obesity incidence rate is smaller. The changes in the *overweight incidence rate* do not only have an impact on the overweight population but also have a second stage impact on the obese population. The changes in the *obesity incidence rate* only have impact on the obese segment of the normoglycemic population. Hence, the changes in the *obesity incidence rate* have lower levels of impact on the diabetic result variables.

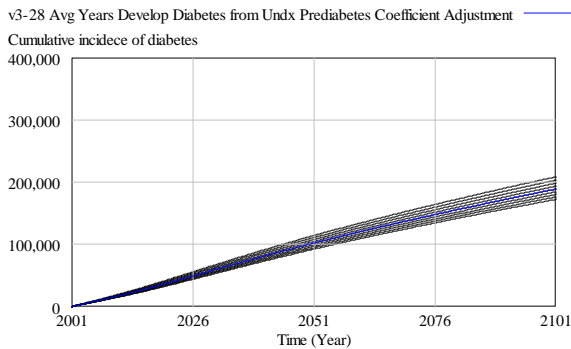




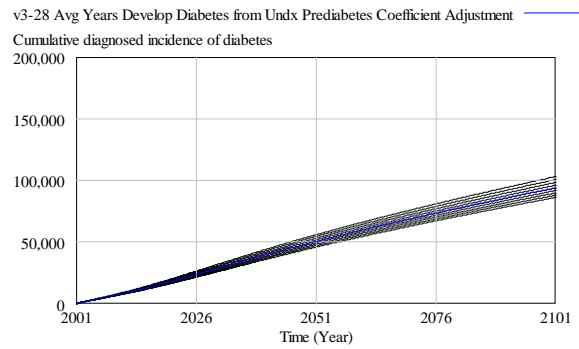
(g)

Figure 7-5. Sensitivity Results for Developing Prediabetes from Obese Population Incidence Rate

Figure 7-5 illustrates one-way sensitivity analysis results for *developing prediabetes from the obese population incidence rate*. We can see that the result variables are very sensitive to the changes in the *developing prediabetes from obese population incidence rate*. The sensitivity graphs exhibit the large variance in the results, especially in the non-cumulative variables. The changes in the prediabetes incidence rate have a direct impact on the undiagnosed prediabetes population, which serves as the headwater of all diabetic population groups. Any change in the undiagnosed prediabetes population will have impact on every downstream diabetic population stock.



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(b)

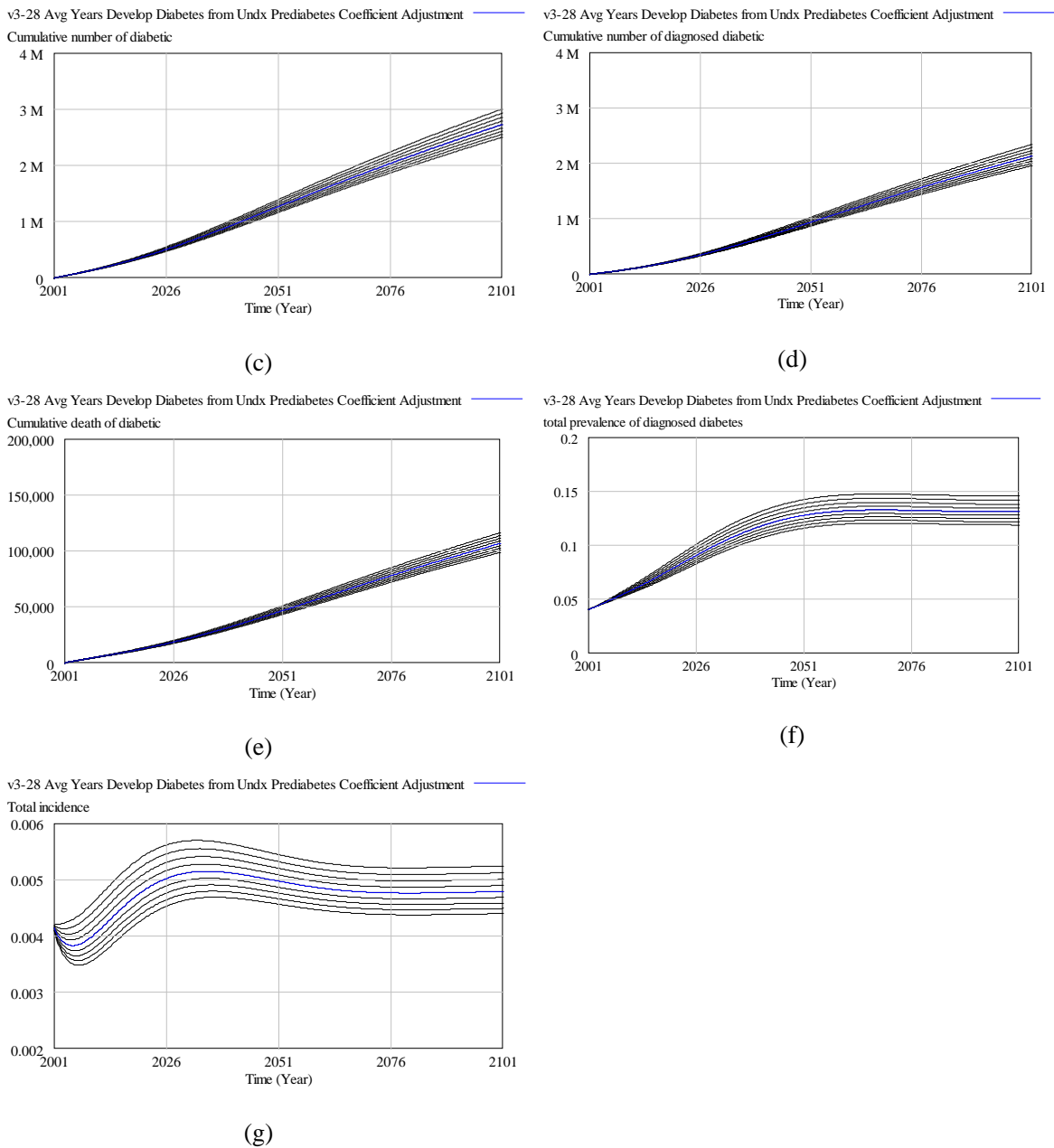
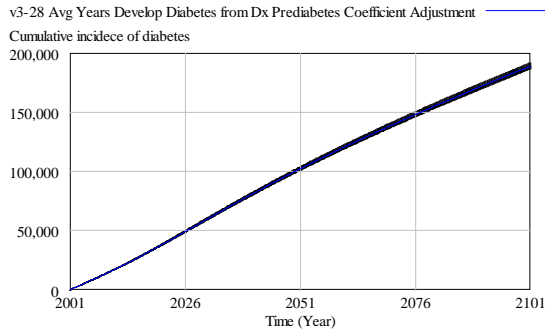


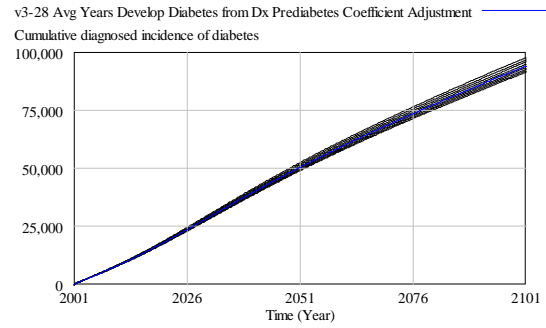
Figure 7-6. Sensitivity Results for Average Years to Develop Diabetes from Undiagnosed Prediabetes

Average years to develop diabetes from undiagnosed prediabetes is another parameter that has a direct impact on the diabetic population. Figure 7-6 illustrates the sensitivity test results for *average years to develop diabetes from undiagnosed prediabetes*. This variable controls the number of undiagnosed prediabetics developing diabetes every year. Changes in the *average years to develop diabetes from undiagnosed prediabetes* have a direct effect on the size of the undiagnosed diabetic population and a secondary effect on the size of the diagnosed diabetic population.

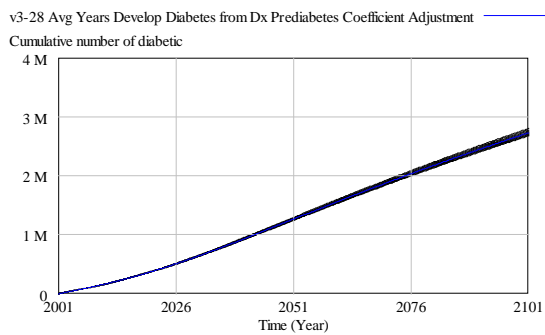
Graph 7-6a to 7-6e show that the cumulative outcome variables are quite sensitive to the changes in the *average years to develop diabetes from undiagnosed prediabetes*. Graph 7-6f and 7-6g show that *total prevalence of diagnosed diabetes* and *total incidence* respond to the changes immediately and in a pronounced fashion.



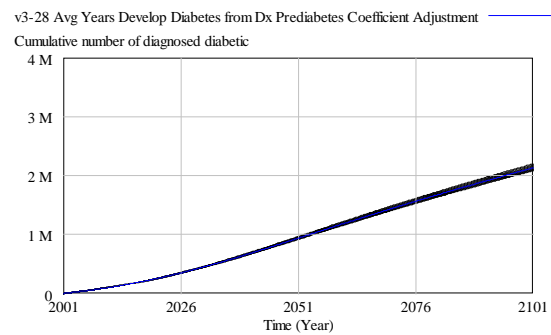
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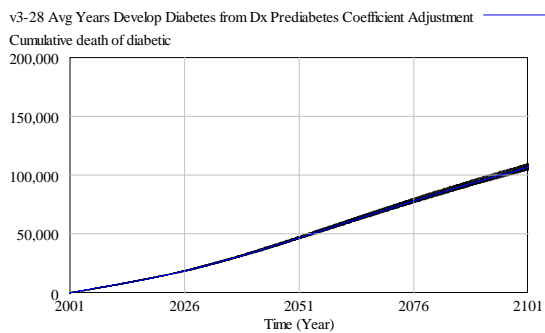
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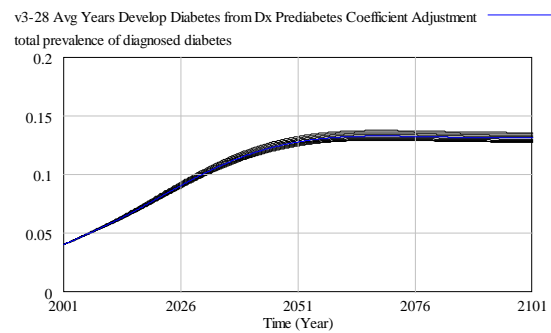
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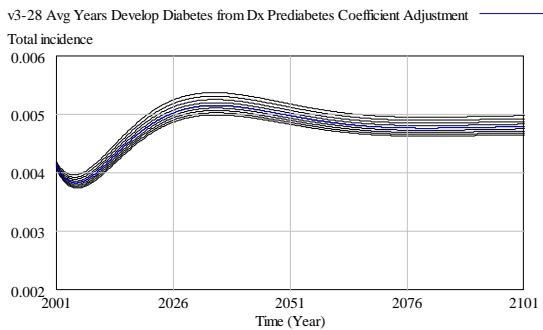
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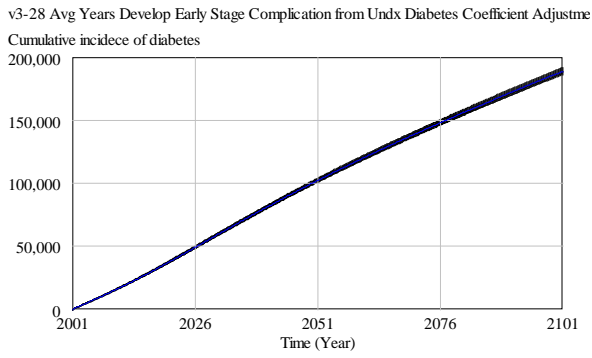


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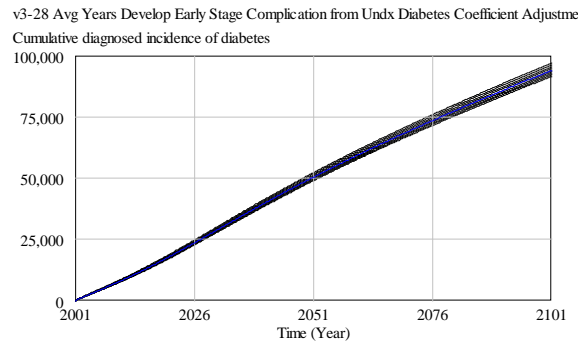
Figure 7-7. Sensitivity Results for Average Years to Develop Diabetes from Diagnosed Prediabetes

Similar to *average years to develop diabetes from undiagnosed prediabetes*, *average years to develop diabetes from diagnosed prediabetes* is another parameter that has a direct impact on the downstream diabetic population. Compared to *average years to develop diabetes from undiagnosed prediabetes*, the *average years to develop diabetes from diagnosed prediabetes* has a lower impact on the outcome variables. As I mentioned in the calibration chapter, *average years to develop diabetes from diagnosed prediabetes* is calibrated from *average years to develop diabetes from undiagnosed prediabetes* by using a constant coefficient. The changes in *average years to develop diabetes from undiagnosed prediabetes* will thus affect the base value of *average years to develop diabetes from diagnosed prediabetes* indirectly. Conversely, the changes in *average years to develop diabetes from diagnosed prediabetes* do not have the same effect on *average years to develop diabetes from undiagnosed prediabetes*. Hence, the outcome variables are less sensitive to the changes in the *average years to develop diabetes from diagnosed prediabetes*.

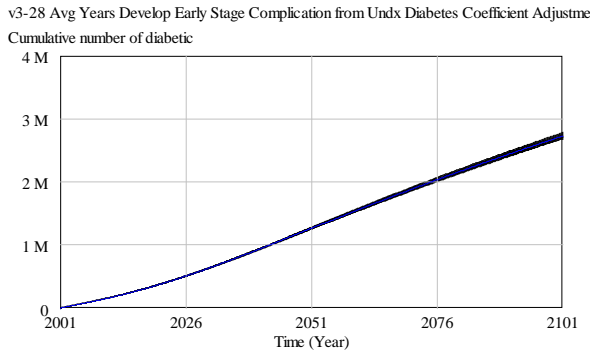
Average years to develop diabetes from diagnosed prediabetes controls the incidence of diabetes from the diagnosed prediabetic population directly. Hence, the changes in *average years to develop diabetes from diagnosed prediabetes* have a large impact on the diabetes incidence related result variables, such as the *cumulative diagnosed incidence of diabetes* and the *total incidence*.



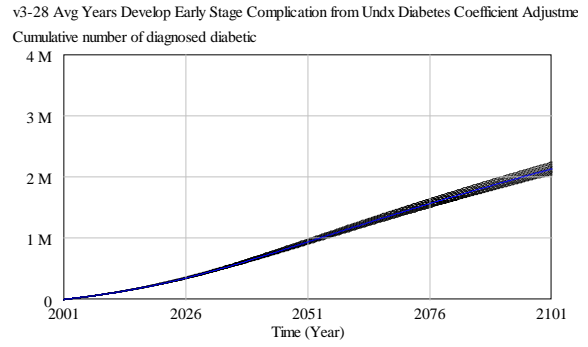
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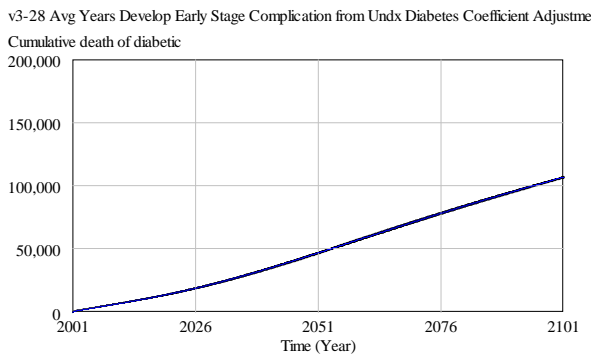
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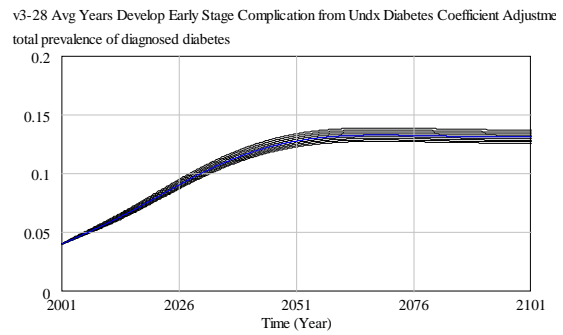
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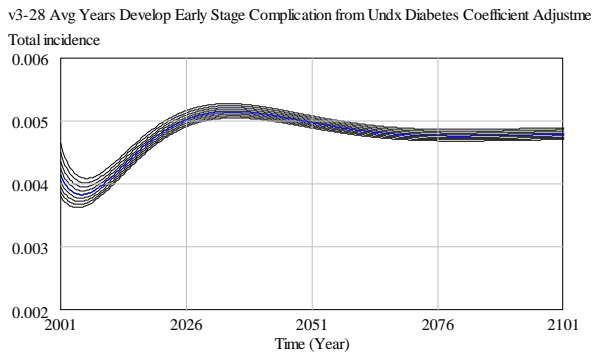
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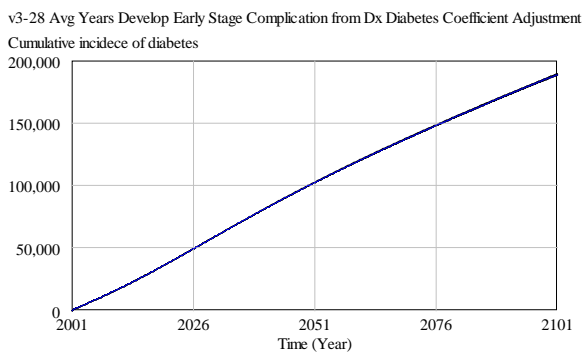
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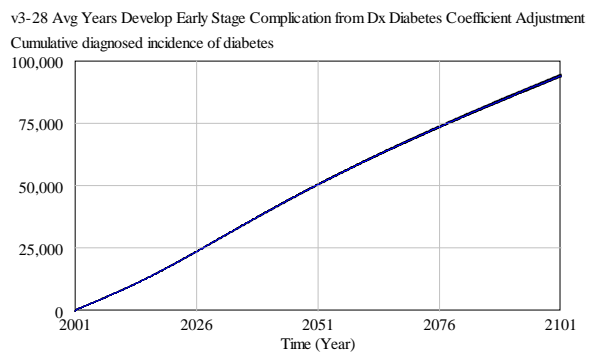
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Figure 7-8. Sensitivity Results for Average Years to Develop Early Stage Complication from Undiagnosed Diabetes

Figure 7-8 shows the sensitivity test results for the *average years to develop early stage complication from undiagnosed diabetes*. The cumulative outcome variables related to the total diabetic population are less sensitive to the changes in the *average years to develop early stage complication from undiagnosed diabetes* when compared to the cumulative outcome variables related to the diagnosed diabetic population. *Average years to develop early stage complication from undiagnosed diabetes* controls the flow rate from the undiagnosed diabetes without complication population to the undiagnosed diabetes with early stage complication population. It will not have large impacts on the total diabetic population since it has nothing to do with diabetes onset. However, the flow from the undiagnosed diabetes without complication population to the undiagnosed diabetes with early complication population is a diagnosis flow according to our definition. As mentioned in the chapter 4, the assumption is that undiagnosed diabetic patients will have their diabetes diagnosed even if the complications are not diagnosed. *Average years to develop early stage complication from undiagnosed diabetes* has direct impacts on the diagnosed diabetic population. Hence, the *cumulative diagnosed incidence*, the *cumulative number of diagnosed diabetic*, the *total prevalence of diagnosed diabetes* and the *total incidence* are more sensitive to the changes in *average years to develop early stage complication from undiagnosed diabetes* compared to other outcome variables.



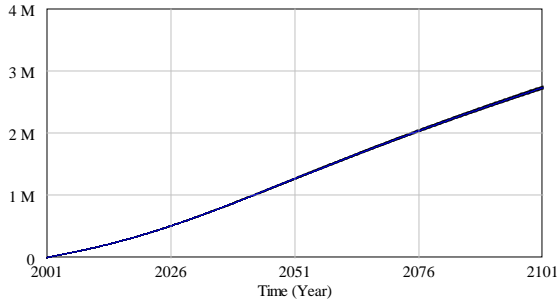
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(b)

v3-28 Avg Years Develop Early Stage Complication from Dx Diabetes Coefficient Adjustment

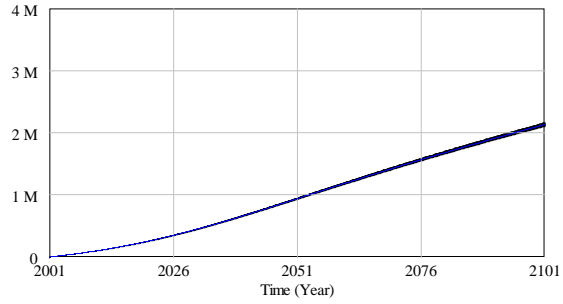
Cumulative number of diabetic



(c)

v3-28 Avg Years Develop Early Stage Complication from Dx Diabetes Coefficient Adjustment

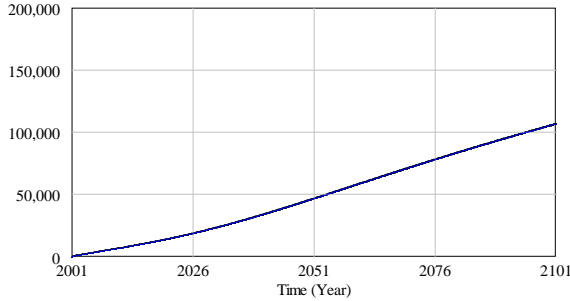
Cumulative number of diagnosed diabetic



(d)

v3-28 Avg Years Develop Early Stage Complication from Dx Diabetes Coefficient Adjustment

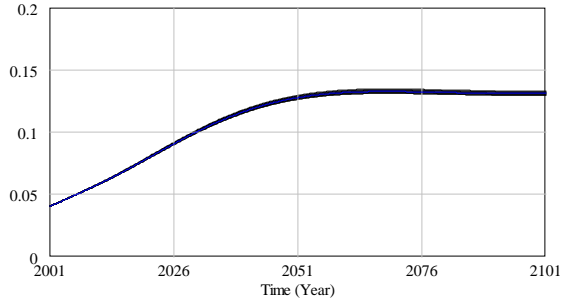
Cumulative death of diabetic



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v3-28 Avg Years Develop Early Stage Complication from Dx Diabetes Coefficient Adjustment

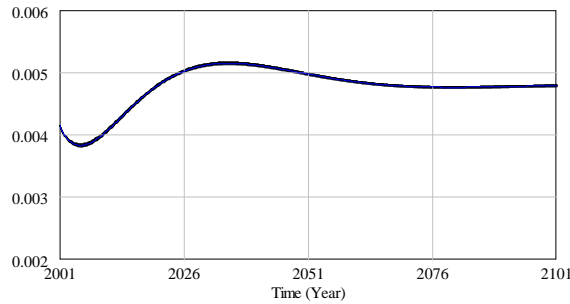
total prevalence of diagnosed diabetes



(f)

v3-28 Avg Years Develop Early Stage Complication from Dx Diabetes Coefficient Adjustment

Total incidence

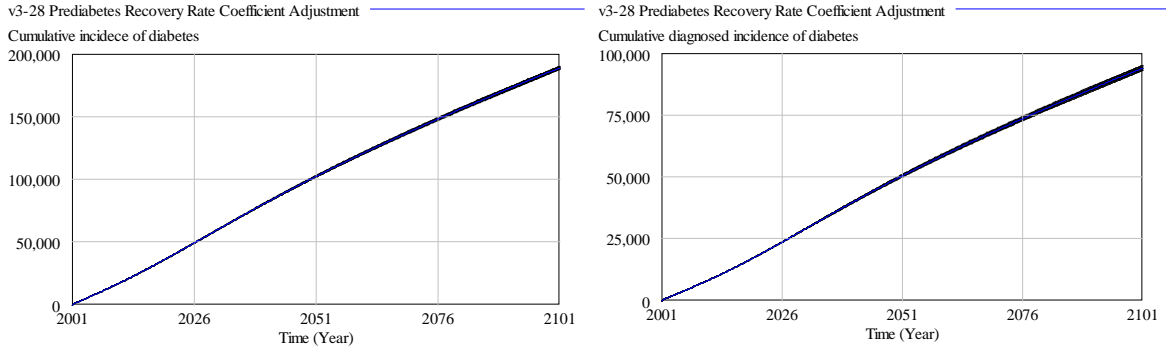


(g)

Figure 7-9. Sensitivity Results for Average Years to Develop Early Stage Complication from Diagnosed Diabetes

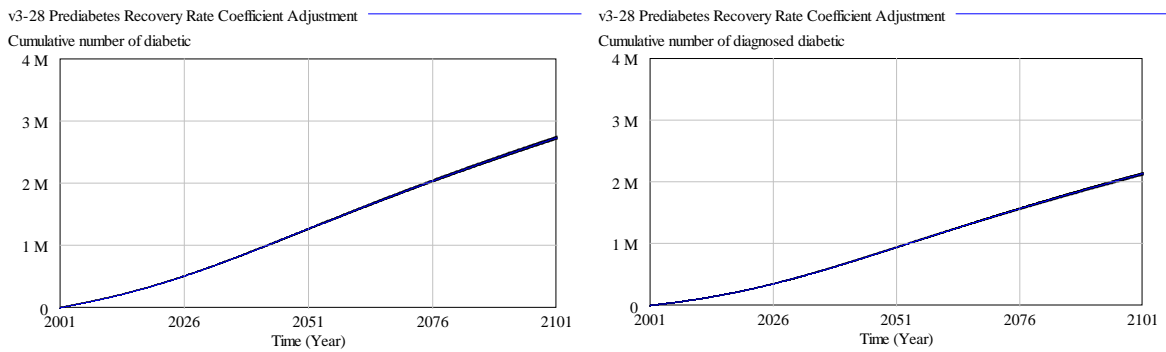
Figure 7-9 illustrates the sensitivity levels of the outcome variable response to the changes in *average years to develop early stage complication from diagnosed diabetes*. From the graphs we can see that the outcome variables are insensitive to the changes in the parameter during my test time period. *Average years to develop early stage complication from diagnosed diabetes* controls the flow from the diagnosed diabetes without complication population to the diagnosed diabetes with early stage macrovascular complication population. The changes in the *average years to develop*

early stage complication from diagnosed diabetes do not affect the number of diabetes or the incidence of diabetes directly since they are diagnosed as diabetic already. The impact on the outcome variables is indirect (e.g. via impact on the total population) and the level of impact is low.



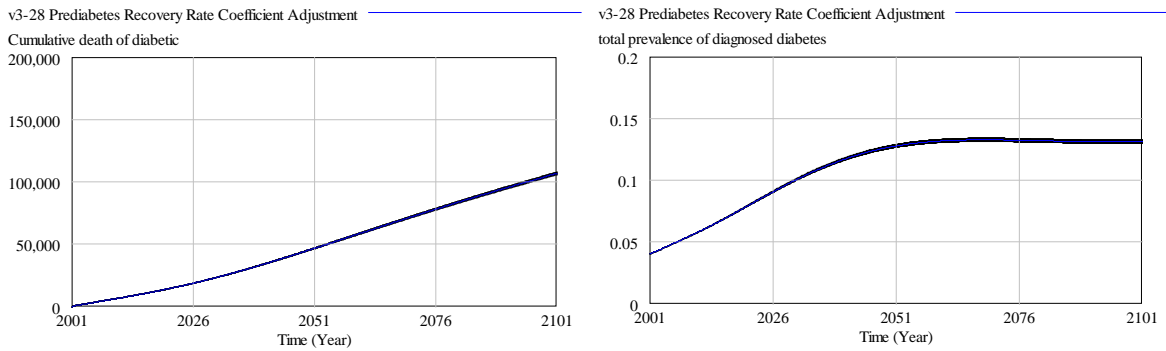
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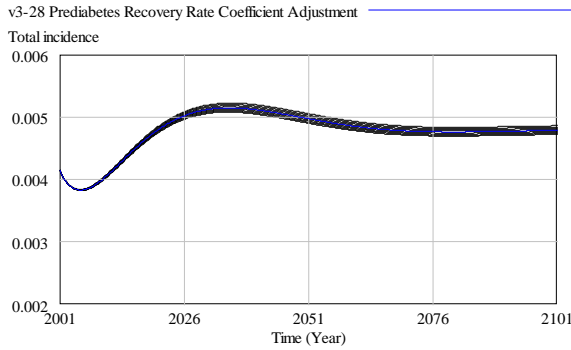
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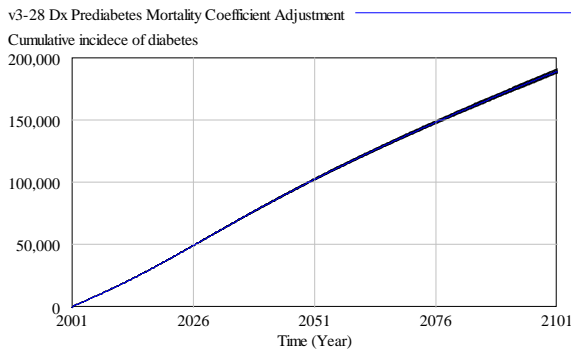
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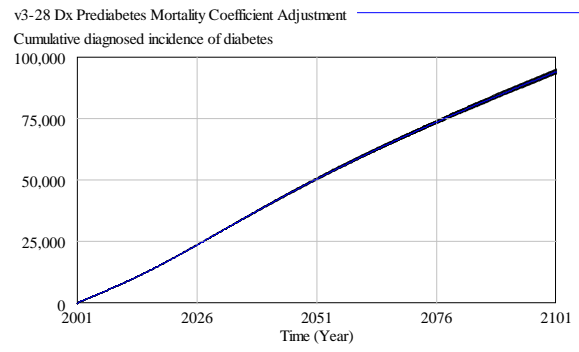
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Figure 7-10. Sensitivity Results for Prediabetes Recovery Rate

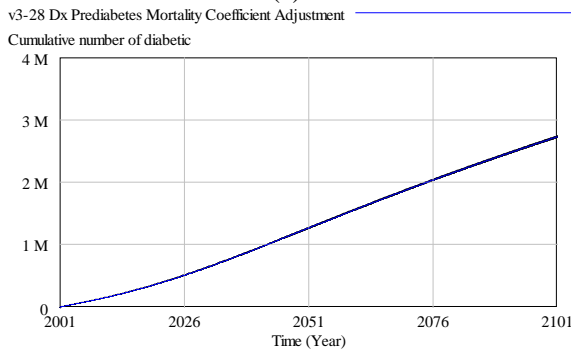
The *prediabetes recovery rate* controls the number of diagnosed prediabetic recovered from hyperglycemia and moving back to the normoglycemic population groups. Figure 7-10 shows that the sensitivity levels of the *prediabetes recovery rate* are mild for the outcome variables. The changes in this parameter have no direct impact on the diabetic population, but they have some levels of impact on the diagnosed prediabetic population and further affect the diabetic population.



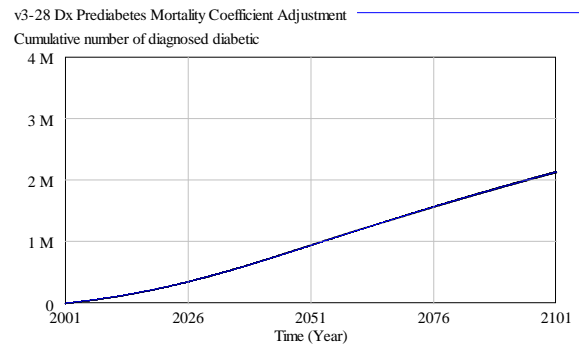
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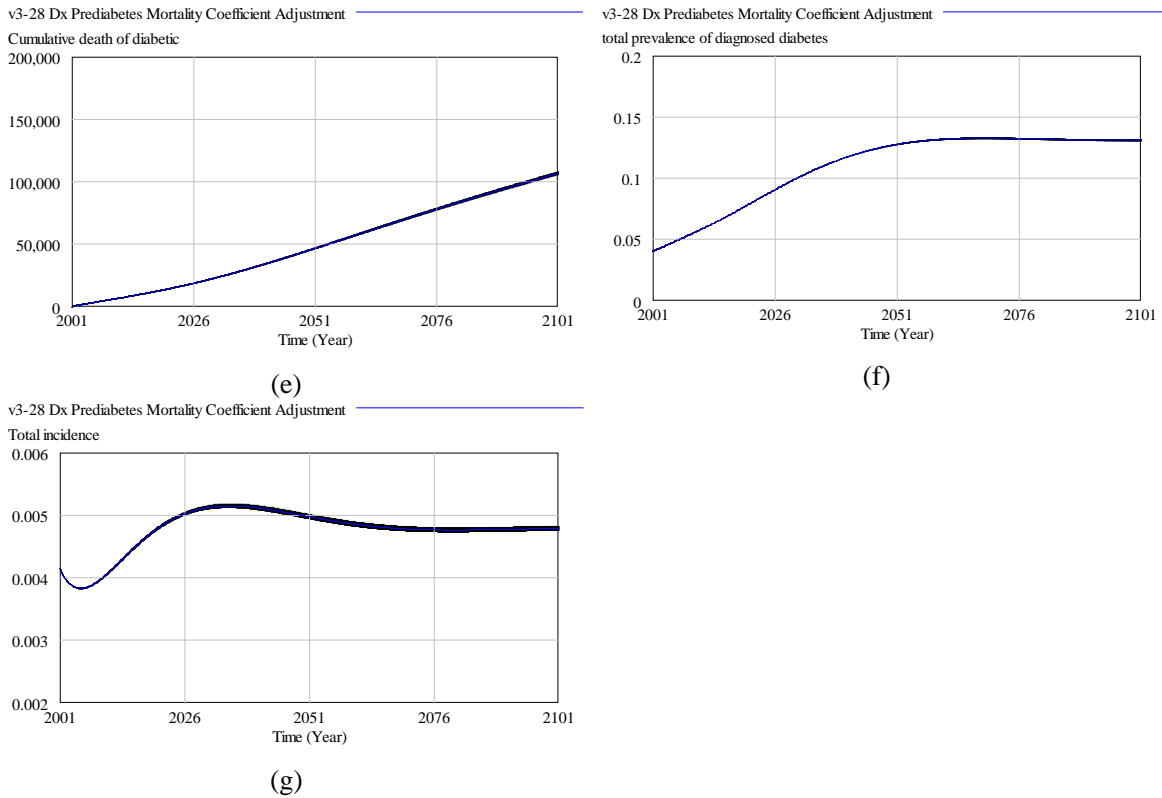
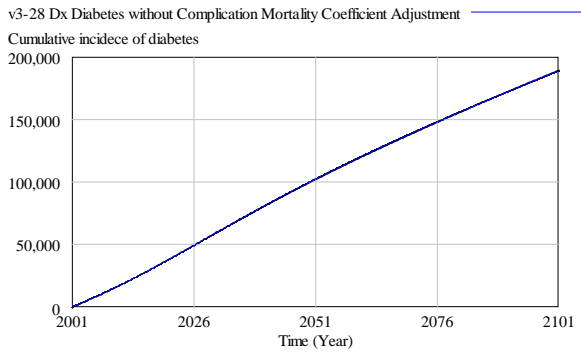
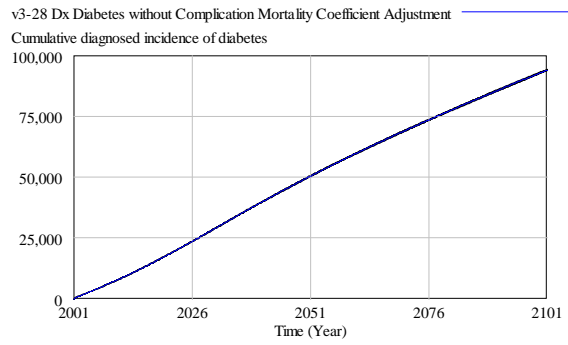


Figure 7-11. Sensitivity Results for Diagnosed Prediabetes Mortality Rate

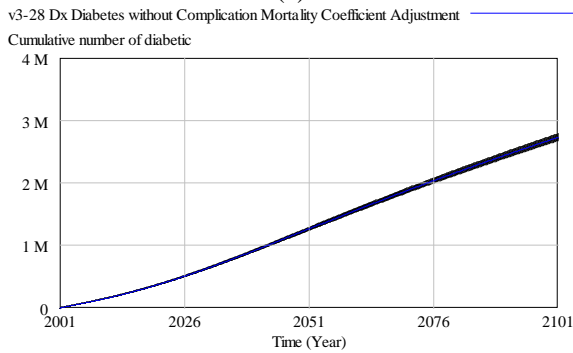
In addition to diabetes progression rates, I also tested the sensitivity of model response to several mortality rates. Graphs in Figure 7-11 show the sensitivity analysis results with respect to the *mortality rate of diagnosed prediabetes*. The changes in the *mortality rate of diagnosed prediabetes* have only a minor impact on the *cumulative incidence of diabetes*, the *cumulative incidence of diagnosed diabetes* and the *total incidence* as shown on Figure 7-11a, 7-11b and 7-11g. The changes in the *mortality rate of diagnosed prediabetes* have a direct impact on the size of the diagnosed prediabetes population, which are the potential new cases of diabetes. Hence, the changes in the test parameter have a secondary impact on the *cumulative incidence of diabetes*, the *cumulative incidence of diagnosed diabetes* and the *total incidence*. The level of impact from changes in the *mortality rate of diagnosed prediabetes* is not obvious on other outcome variables.



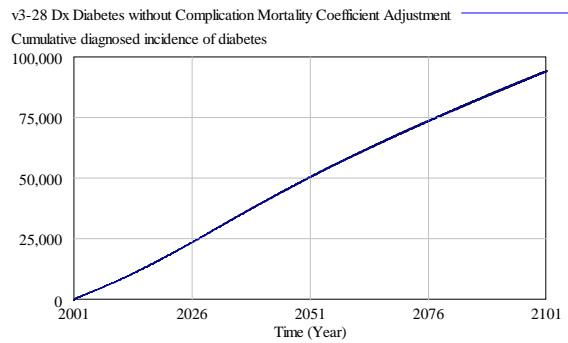
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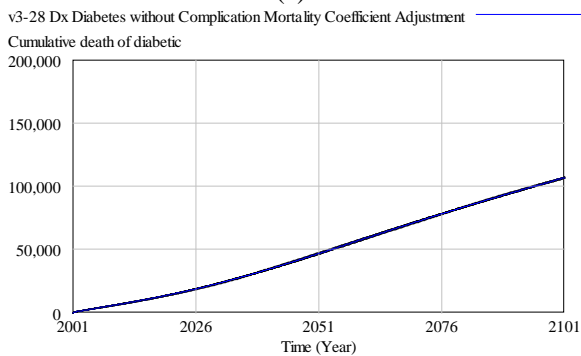
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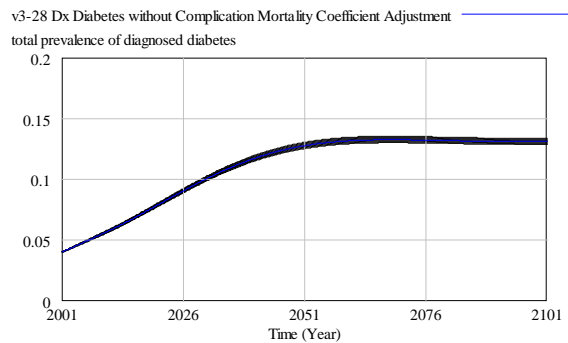
(c)



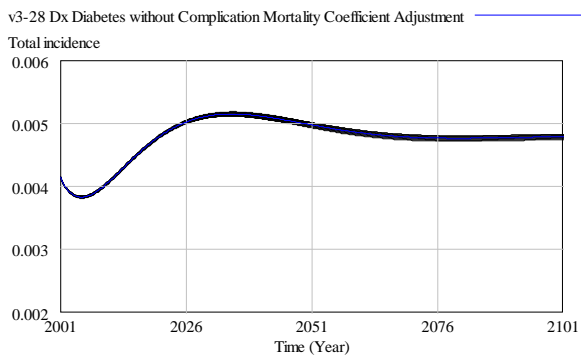
(d)



(e)



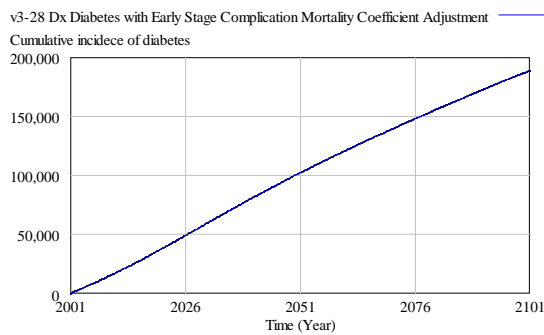
(f)



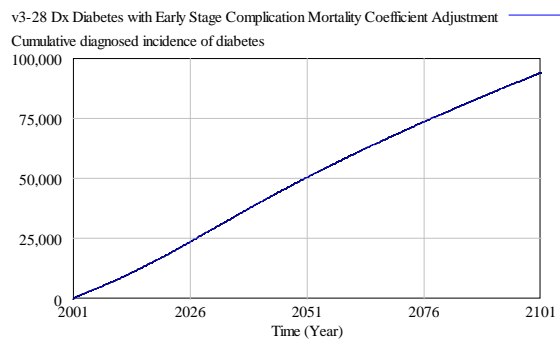
(g)

Figure 7-12. Sensitivity Results for Mortality Rate of Diagnosed Diabetes without Complication

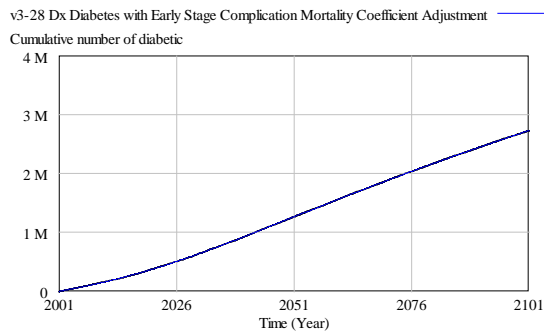
Figure 7-12 illustrates the sensitivity analysis results for *mortality rate of diagnosed diabetes without complication*. This test variable has a direct impact on the *cumulative death of diabetic*. Figure 7-12e shows that the *cumulative death of diabetic* is relatively sensitive to changes in the *mortality rate of diagnosed diabetes without complication* from the beginning of the simulation. The test variable also has a direct impact on the size of the diagnosed diabetics without complication population. Hence, the *cumulative number of diabetic* and the *total prevalence of diagnosed diabetes* are also relatively sensitive to changes in the *mortality rate of diagnosed diabetes without complication*. However, the sensitivity levels are not high due to the low mortality rate and the relatively small population in the diagnosed diabetes without complication population group.



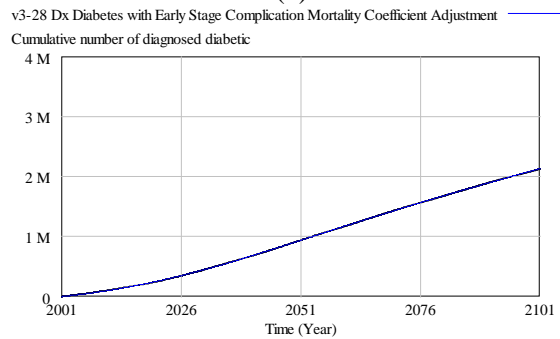
(a)



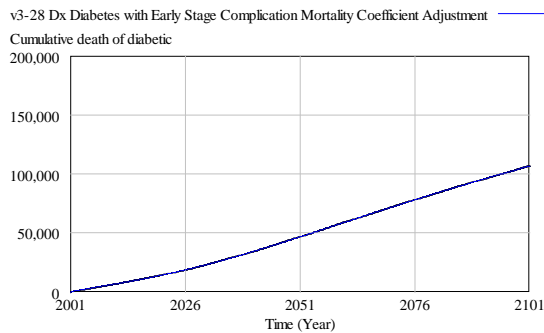
(b)



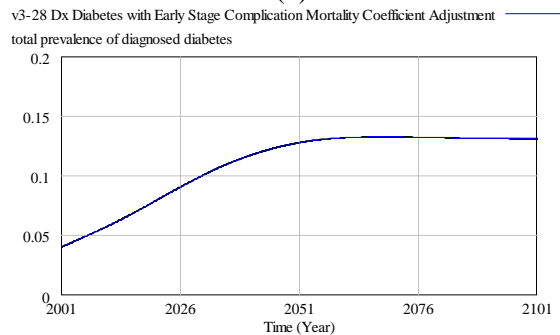
(c)



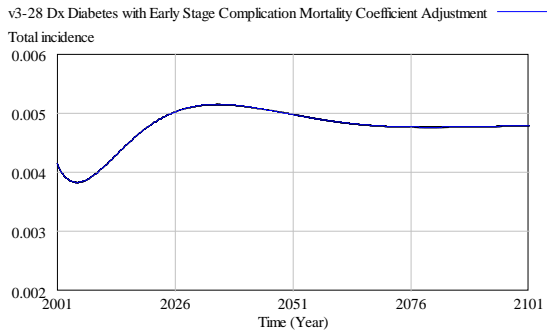
(d)



(e)



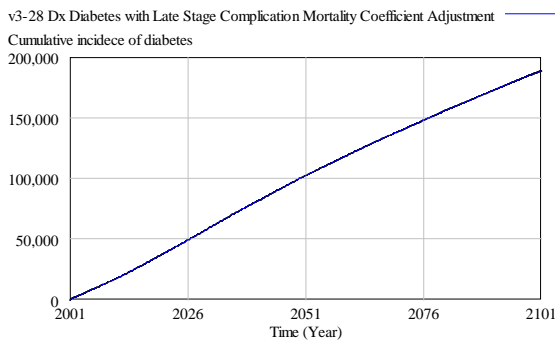
(f)



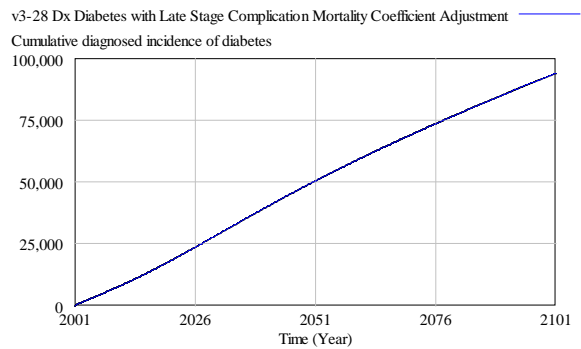
(g)

Figure 7-13. Sensitivity Results for Mortality Rate of Diagnosed Diabetes with Early Stage Complication

Figure 7-13 shows the sensitivity test results for the *mortality rate of diagnosed diabetes with early stage complication*. Like other mortality rates, the *mortality rate of diagnosed diabetes with early stage complication* has a direct impact on the corresponding population (here, diagnosed diabetics with early stage macrovascular complications). However, the levels of impacts are not obvious in the graphs. The diagnosed diabetes with early stage macrovascular complication population is a small fraction of the total diabetic population. The changes in the diagnosed diabetes with early stage macrovascular complication population only cause small changes on the outcome variables. Hence, the outcome variables are very insensitive to the changes in the *mortality rate of diagnosed diabetes with early stage complication* as shown in Figure 7-13.



(a)



(b)

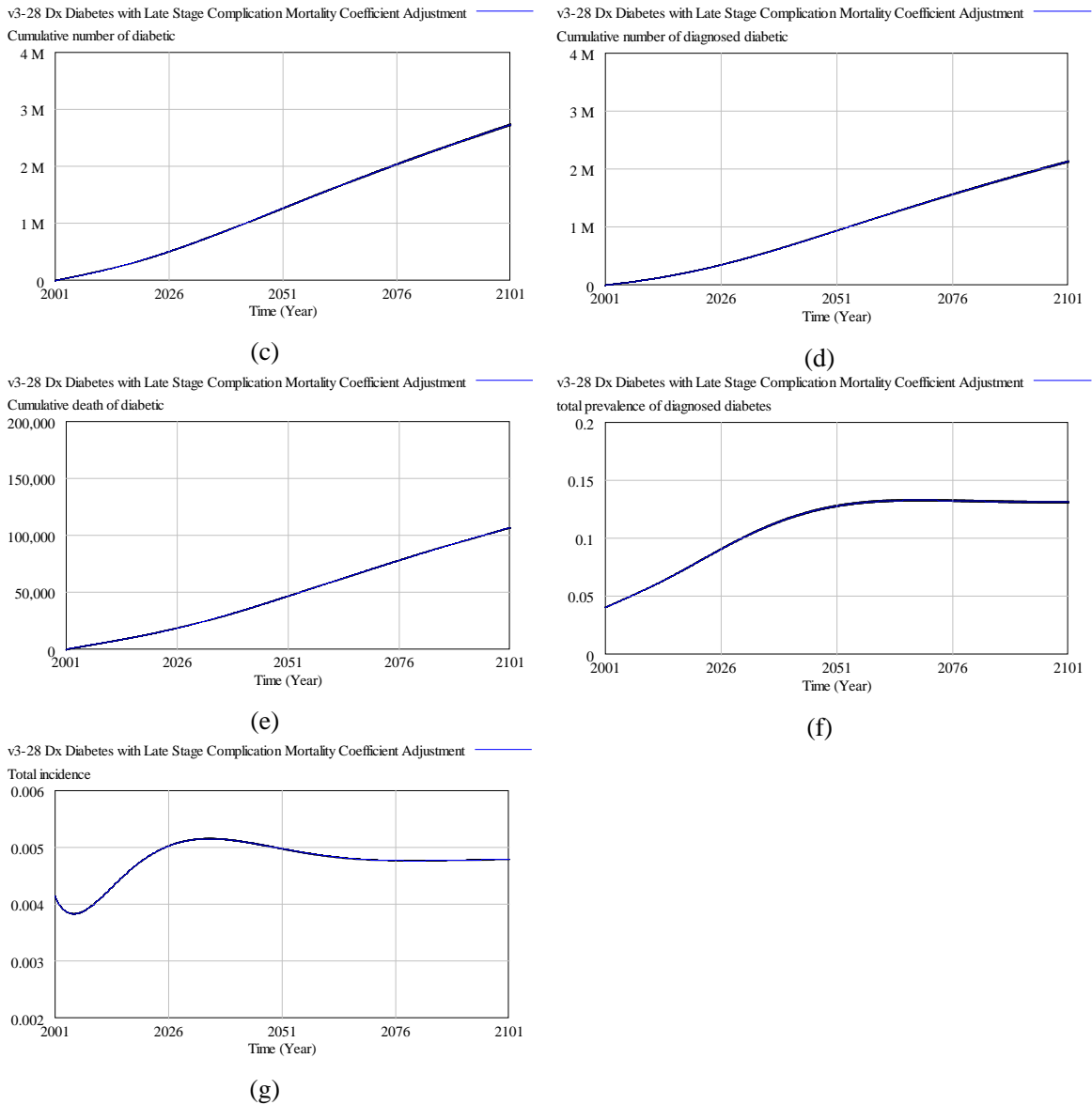


Figure 7-14. Sensitivity Results for Mortality Rate of Diagnosed Diabetes with Late Stage Complication

Similar to the *mortality rate of diagnosed diabetes with early stage complication*, the changes in the *mortality rate of diagnosed diabetes with late stage complication* do not have an obvious impact on any result variable due to the small population base as shown in Figure 7-14.

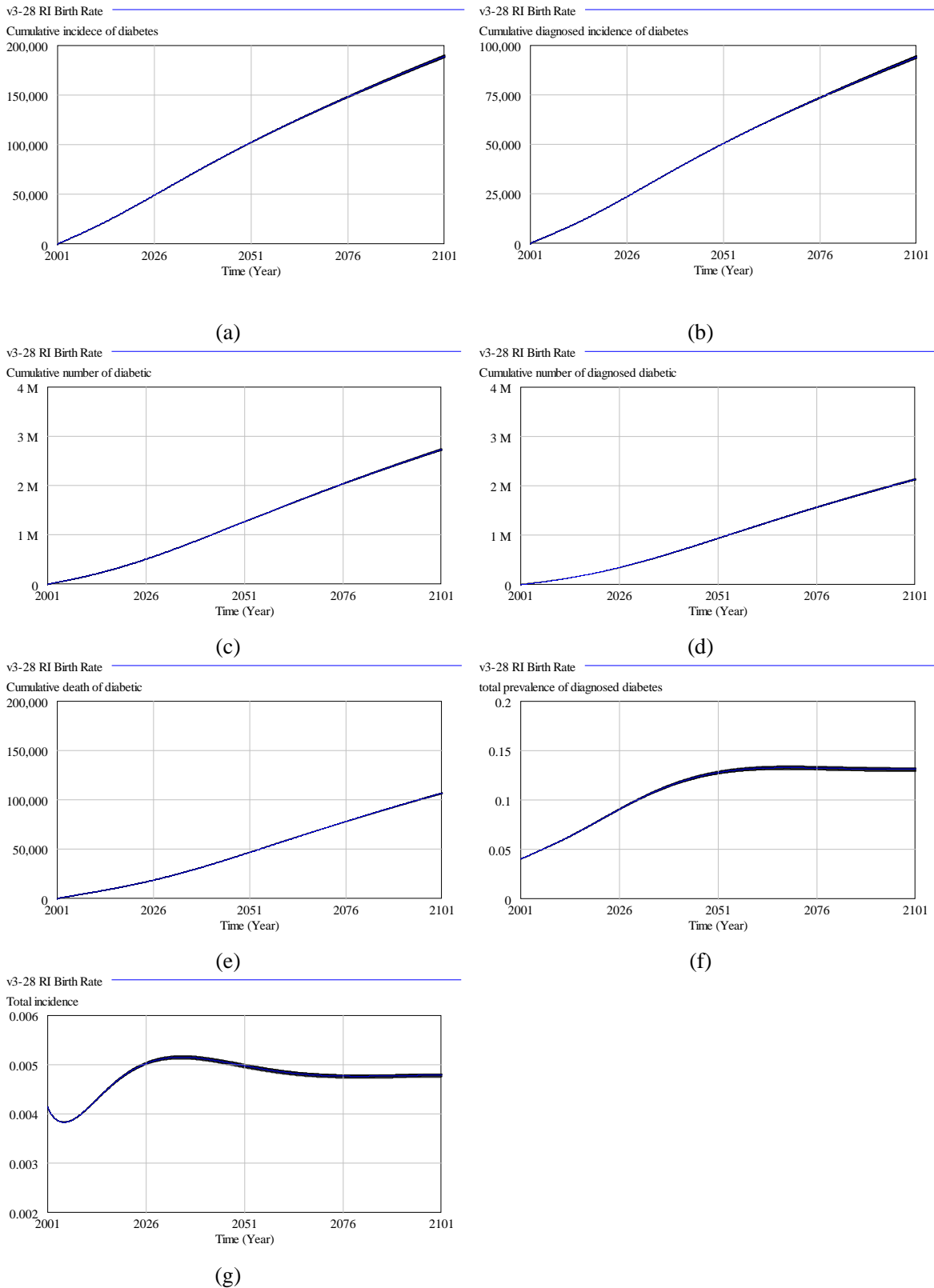


Figure 7-15. Sensitivity Results for SHR Birth Rate of Aboriginal Population

As previously described in chapter 6, I made the assumption that the Aboriginal population has the same birth rate with the non-Aboriginal population due to insufficient

data. However, it is a well known fact that the Aboriginal population has a higher birth rate than the general population in the SHR. Hence, I tested the sensitivity level of the result variables in response to changes in assumption regarding the birth rate of the Aboriginal population. Figure 7-15 shows the changes in the result variables as a result of changes in the Aboriginal component of the population birth rate variable. The changes in the SHR birth rate of Aboriginal population do not impose heavy impacts on the result variables, and the assumption of using the same birth rate for the Aboriginal population is therefore not expected to strongly distort simulation results.

After conducting sensitivity analysis for a single variable, we have gained some basic understanding on the questions “what kind of impact could happen from the changes in model parameter” and “what levels of impact could each test parameter cause”. In general, changes in the upstream variables could lead to heavier impacts on the diabetes burdens than changes in the downstream variables. For instance, changes in the *mortality rate of diagnosed diabetes without complication* have larger impacts on the result variables than the changes in the *mortality rate of diagnosed diabetes with early stage complication*. Also, the changes on the rates, which are applied to a large population group, could have heavier impacts on the diabetes burdens than the changes on the rates when applied to a small population group. For instance, changes in the *average years to develop diabetes from undiagnosed prediabetes* impose a larger impact than do changes in the *average years to develop early stage complication from diagnosed diabetes*.

Nevertheless, the impacts from the changes in single variables are limited. Can we amplify the impact if we change multiple variables at the same time? Is the level of impact stronger or weaker than the level of impact by just adding the effects? What variables can we alter together? What variable combination can achieve maximum effects? In order to answer these questions, I performed multi-variable sensitivity analysis after single-variable sensitivity analysis.

7.1.2 Multi-variable Sensitivity Analysis

Theoretically, we could change all variables in the model together to achieve the maximum effects. However, it is rarely feasible to do that in practice. First of all, not all variables in the model are feasible or ethical to change (consider affecting the birth rate). Secondly, it may be too costly to undertake a sufficient number of simultaneous interventions to affect all variables together. With limited resources, decision makers

must select and target certain focus areas carefully to optimize the utility while maintaining the feasibility of interventions.

I proposed several combinations of variables based on the results from the single-variable sensitivity analysis. Each variable combination could plausibly be altered by one intervention policy. Then I tested the sensitivity levels of result variables response to the changes in the variable combinations. By observing and analyzing the responses, we can develop potential intervention policies to aid in lowering the diabetes prevalence and diabetes incidence rate.

Variables in each combination are altered independently during the multi-variable sensitivity analysis. Effect from each variable could reinforce each other or could cancel out each other. For instance, we have the scenario that the overweight incidence rate is raised to the maximum level and the obesity incidence rate is lowered to the minimum level at the same time. We also have the scenario that both the overweight incidence and the obesity incidence rate are raised to the maximum level.

Table 7-1. Variable Combinations for Multi-variable Sensitivity Analysis

Variable Combination	Potential Intervention
Overweight incidence rate & obesity incidence rate	Better weight management for the normoglycemic population
Prediabetes diagnosis rate & diabetes diagnosis rate	Better hyperglycemia diagnosis
Average years to develop diabetes from undiagnosed prediabetes & average years to develop diabetes from diagnosed prediabetes	Better prediabetes management
Develop prediabetes from obese population incidence rate & prediabetes incidence rate	Better weight management (e.g. through improved physical activity and nutrition) for high risk population groups
Average years to develop early stage complication from diagnosed diabetes & mortality of diagnosed diabetes without complication population	Better diabetes management
Mortality of diagnosed diabetes with early stage complication population & mortality of diagnosed diabetes with late stage complication population	Better diabetes complication treatment
Prediabetes diagnosis rate & prediabetes recovery rate + average years to develop diabetes from diagnosed prediabetes	Comprehensive prediabetes management

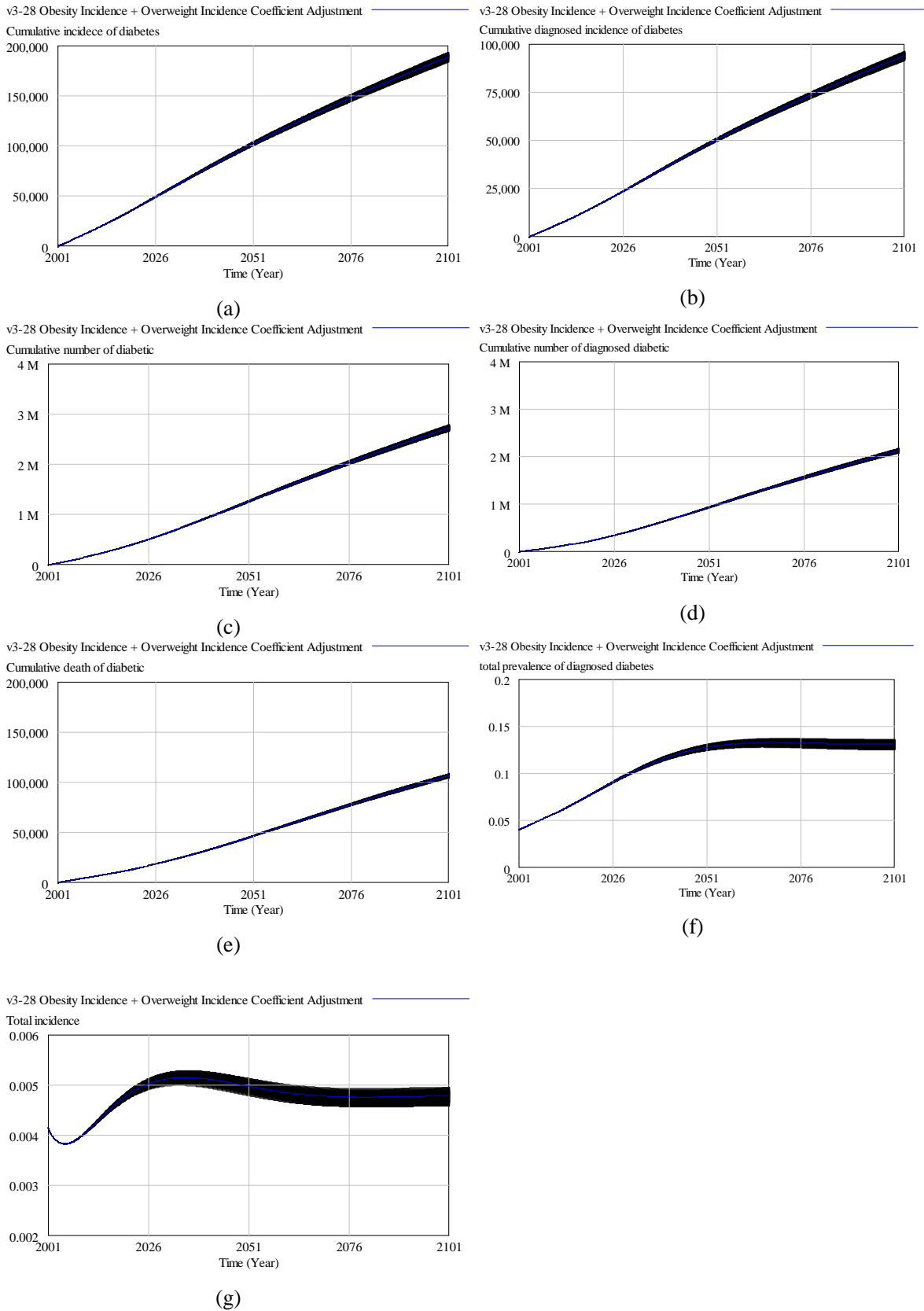
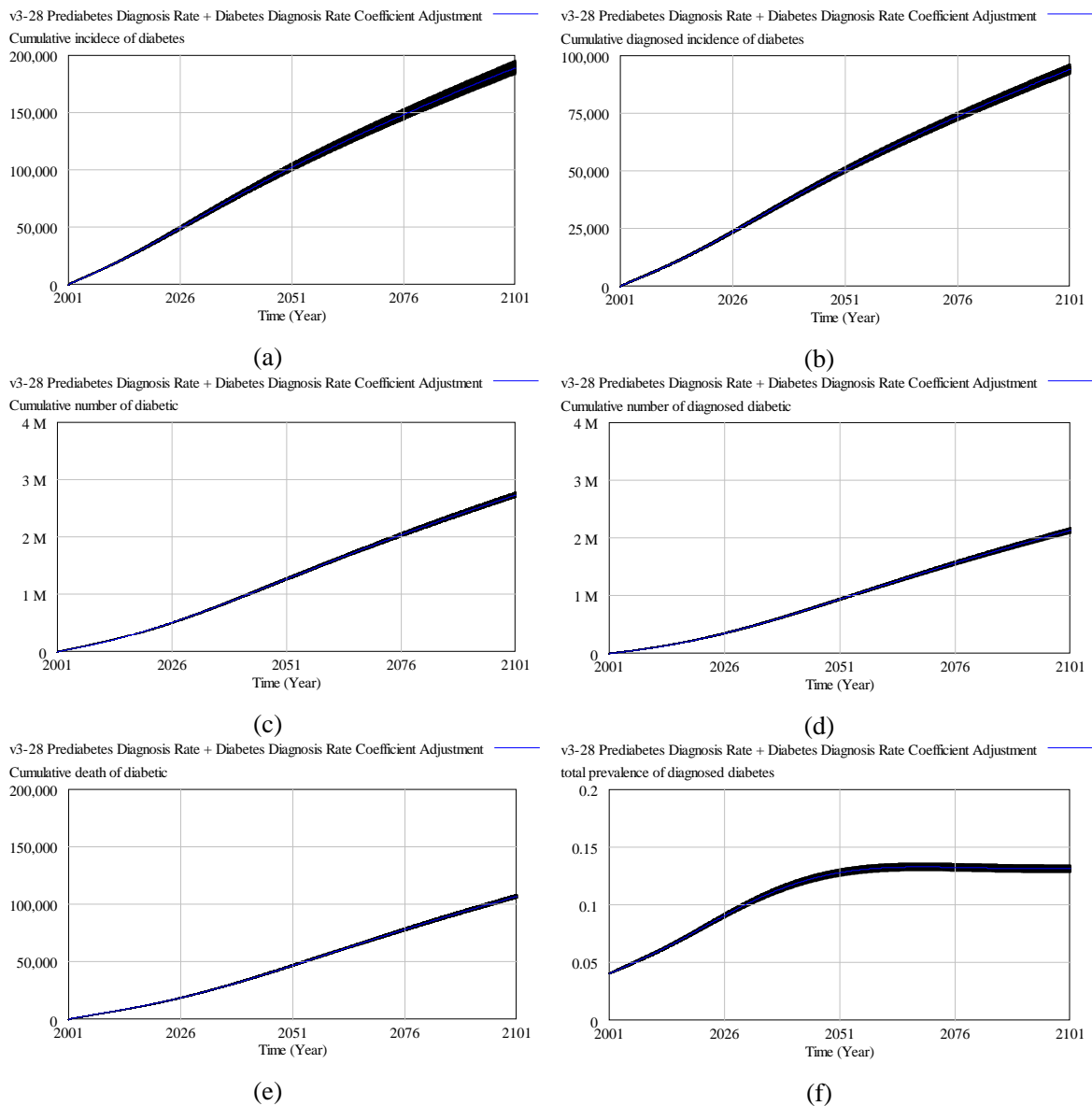
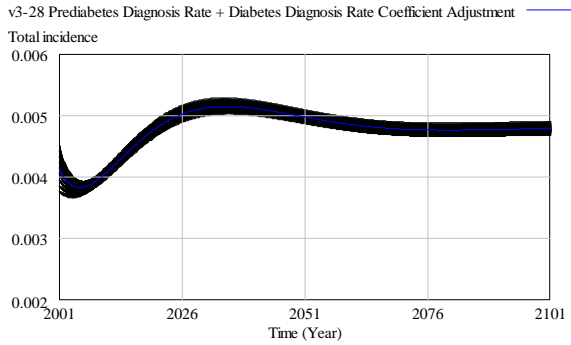


Figure 7-16. Sensitivity Results for Overweight Incidence Rate and Obesity Incidence Rate

The first variable combination I tested is the combination of the *overweight incidence rate* and the *obesity incidence rate*. The changes in this variable combination can be achieved by weight management programs. Figure 7-16 illustrates the sensitivity levels of outcome variables response to the changes in the *overweight incidence rate* and the *obesity incidence rate* combination. The changes in this variable combination have moderate levels of impacts on the diabetes incidence and the number of diabetic as shown in figures from 7-16a to 7-16d. The changes also have relatively low level impacts on the *cumulative death of diabetic*. However, the changes have high level impacts on the non-cumulative result variables in long run, especially on the *total incidence*.

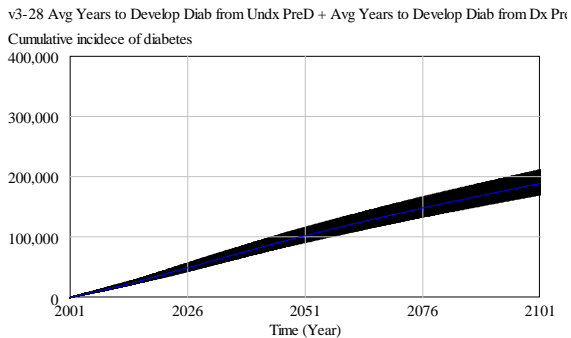




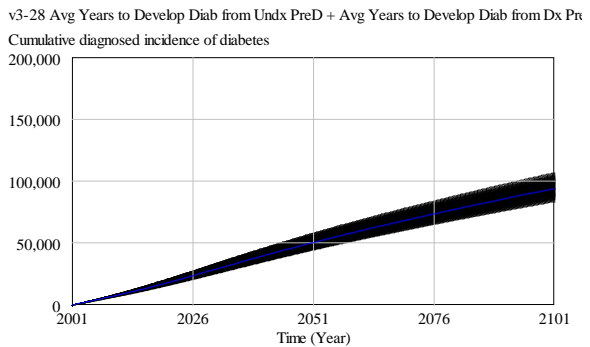
(g)

Figure 7-17. Sensitivity Results for Prediabetes Diagnosis Rate and Diabetes Diagnosis Rate

Figure 7-17 shows the sensitivity analysis results for the *prediabetes diagnosis rate* and the *diabetes diagnosis rate* combination. The changes in this combination directly targeted on the prediabetes incidence and diabetes incidence. Graphs 7-17a and 7-17b show that the changes have heavy impacts on the cumulative incidence of diabetes and the cumulative diagnosed incidence of diabetes. The impacts on the diabetes incidence are also reflected from the changes in the *total incidence* as shown in Figure 7-17g. The *total incidence* shows a large variance at the beginning of the simulation. Changes in the diabetes diagnosis rate have a direct impact on the total incidence. A high diabetes diagnosis rate could lead to a lot of undiagnosed diabetic patients becoming diagnosed initially. The size of undiagnosed diabetic population become much smaller than before after the initial diagnosis and will result in a fewer number of patients are diagnosed. The oscillation finally reaches an equilibrium state in the long run as the variance converges in Figure 7-17g.



(a)



(b)

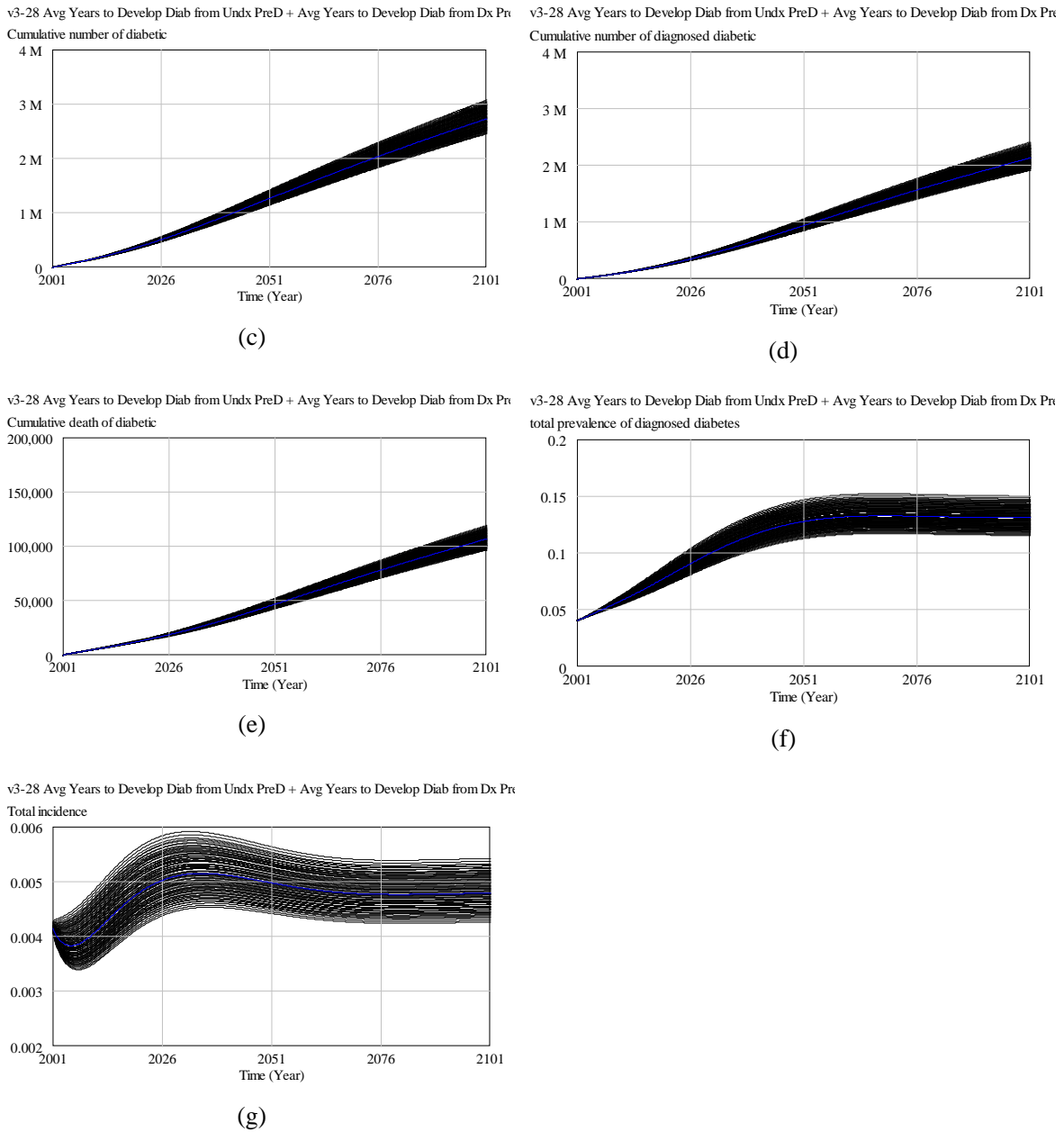


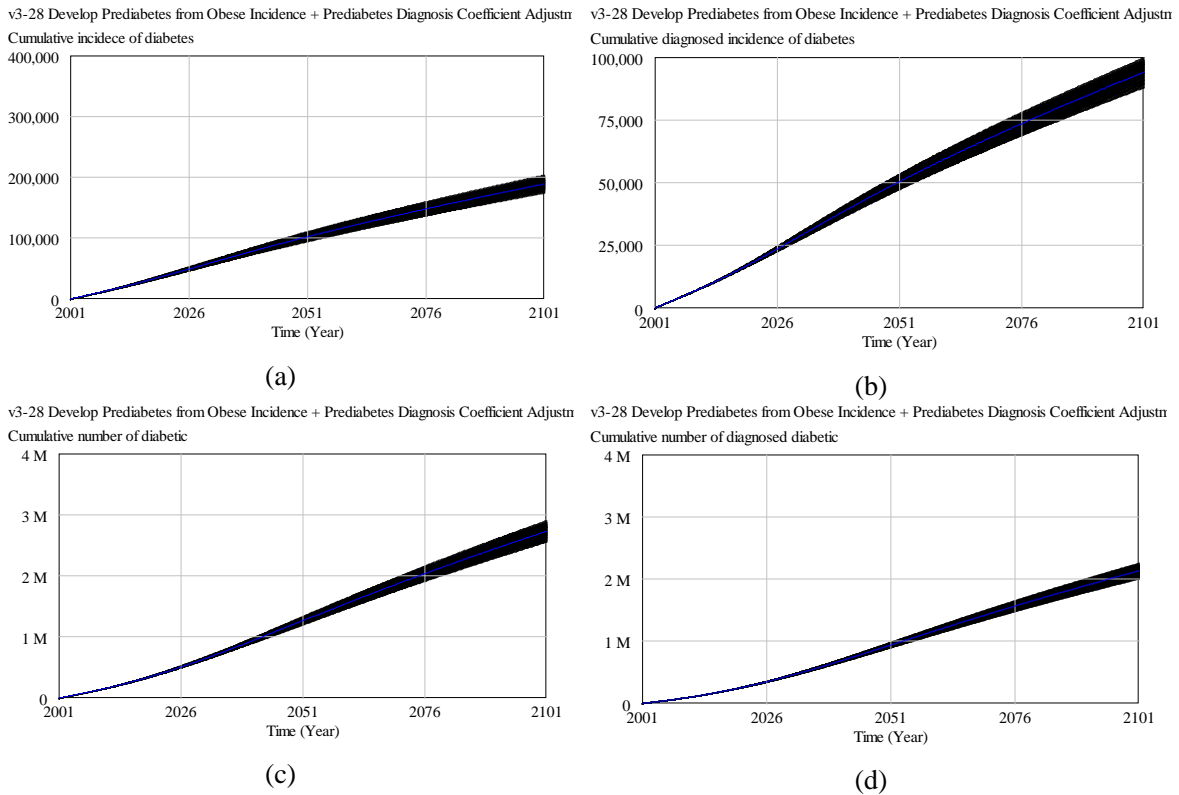
Figure 7-18. Sensitivity Results for Average Years to Develop Diabetes from Undiagnosed Prediabetes and Average Years to Develop Diabetes from Diagnosed Prediabetes

The combination of simultaneous changes to the *average years to develop diabetes from undiagnosed prediabetes* and the *average years to develop diabetes from diagnosed prediabetes* has a direct impact on the diabetes incidence and the diabetes prevalence. The *average years to develop diabetes from undiagnosed prediabetes* controls the number of undiagnosed prediabetic becoming diabetic in the model. It has the direct impact on the count of diabetic and diabetes cases occurring per year. It also

has secondary effects on the *average years to develop diabetes from diagnosed prediabetes* since the base value of the *average years to develop diabetes from diagnosed prediabetes* is calibrated from the *average years to develop diabetes from undiagnosed prediabetes*.

Additional to the changes in the *average years to develop diabetes from undiagnosed prediabetes*, we change the value of the *average years to develop diabetes from diagnosed prediabetes* independently even though the base value is dependent on the value of the *average years to develop diabetes from undiagnosed prediabetes*. The *average years to develop diabetes from diagnosed prediabetes* controls the number of diagnosed prediabetic becomes diabetic in the model. It has the direct impact on the count of diabetic and diabetes incidence as well.

This combination has significant impacts on every result variable as shown in Figure 7-18. The level of impact from the variable combination is higher than individual variable when varied in isolation (as seen in Figure 7-6 and 7-7), but very close to the sum of impacts from individual variables.



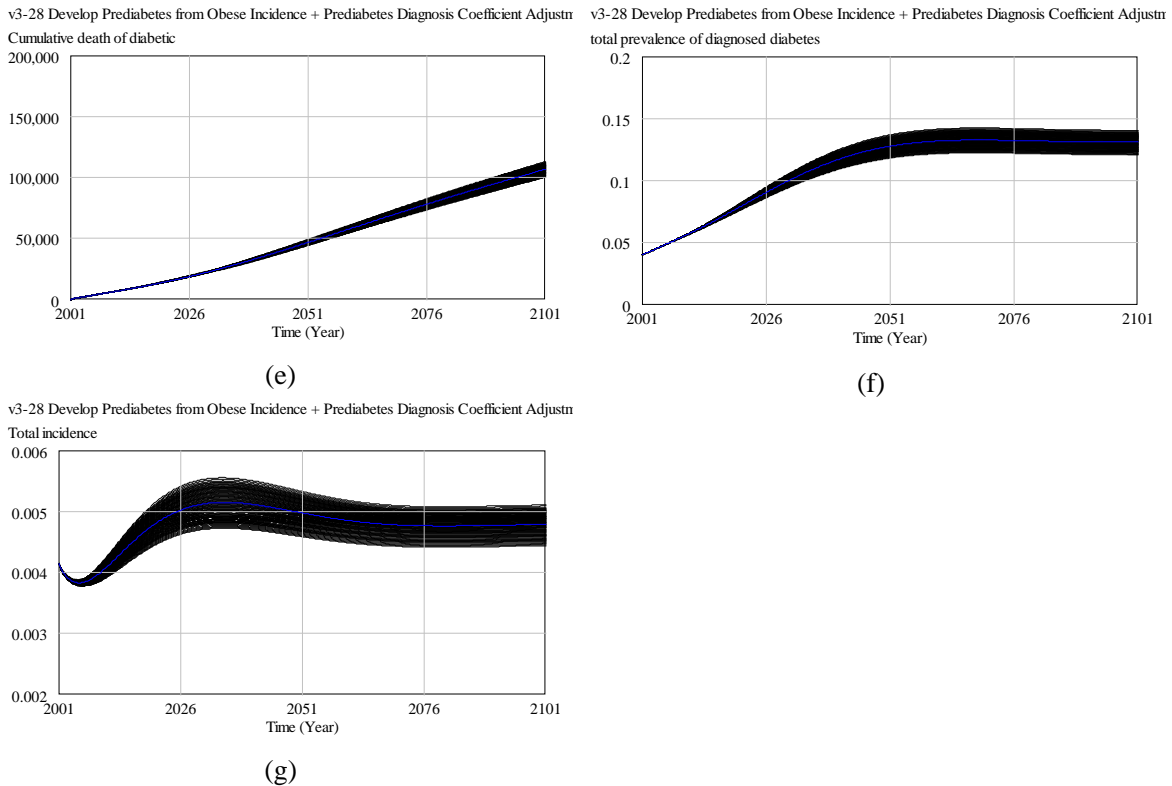
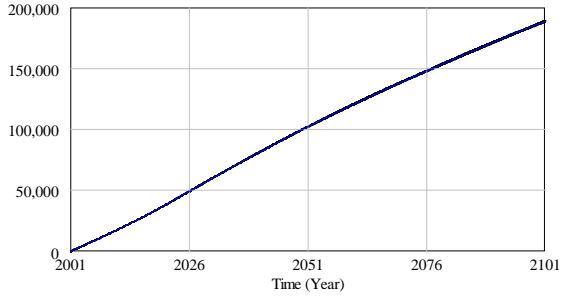


Figure 7-19. Sensitivity Results for Develop Prediabetes from Obese Incidence Rate and Prediabetes Diagnosis Rate

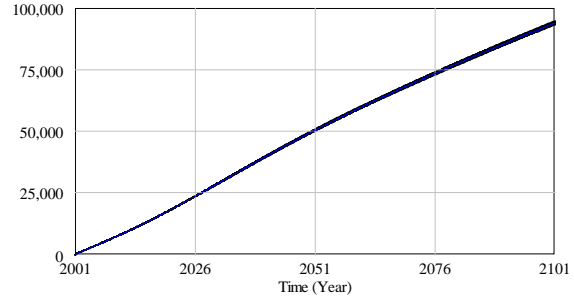
Figure 7-19 illustrates sensitivity results for changes in the combination of the *develop prediabetes from obese incidence rate* and the *prediabetes diagnosis rate*. This variable combination has a focus on the prediabetic population, which is the headwater of the diabetic population. Changes in the *develop prediabetes from obese incidence rate* affect the undiagnosed prediabetic population and the changes in the *prediabetes diagnosis rate* directly impact the diagnosed prediabetic population. Although the changes do not directly impact the diabetic population, they still have heavy secondary impacts on the outcome variables as shown in Figure 7-19.

v3-28 Avg Years to Develop Early Comp from Dx Diab + Mortality Dx Diab without Comp Co
Cumulative incidence of diabetes



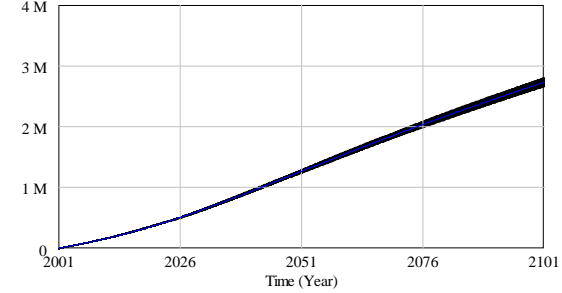
(a)

v3-28 Avg Years to Develop Early Comp from Dx Diab + Mortality Dx Diab without Comp Co
Cumulative diagnosed incidence of diabetes



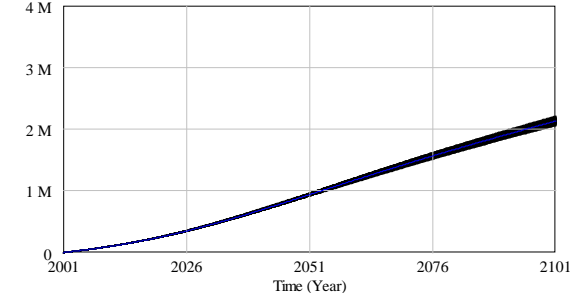
(b)

v3-28 Avg Years to Develop Early Comp from Dx Diab + Mortality Dx Diab without Comp Co
Cumulative number of diabetic



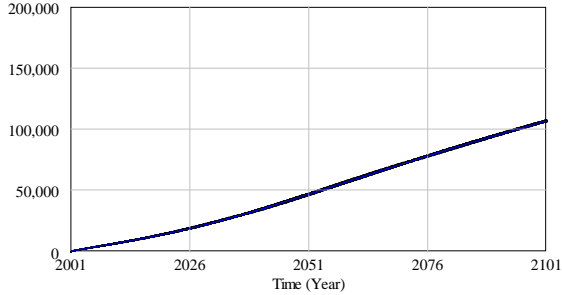
(c)

v3-28 Avg Years to Develop Early Comp from Dx Diab + Mortality Dx Diab without Comp Co
Cumulative number of diagnosed diabetic



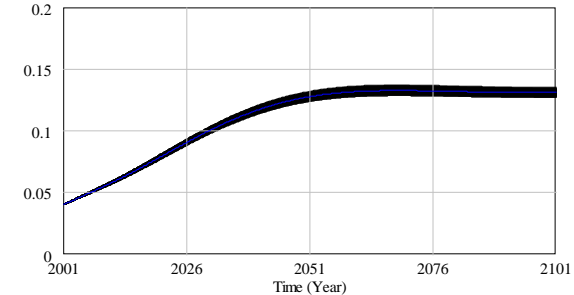
(d)

v3-28 Avg Years to Develop Early Comp from Dx Diab + Mortality Dx Diab without Comp Co
Cumulative death of diabetic



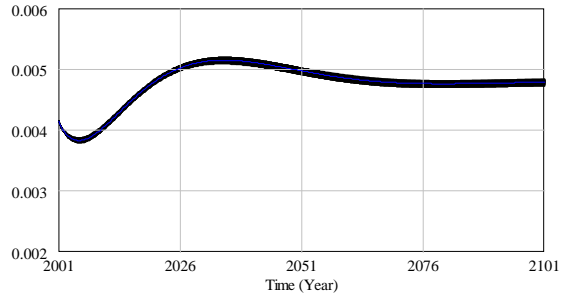
(e)

v3-28 Avg Years to Develop Early Comp from Dx Diab + Mortality Dx Diab without Comp Co
total prevalence of diagnosed diabetes



(f)

v3-28 Avg Years to Develop Early Comp from Dx Diab + Mortality Dx Diab without Comp Co
Total incidence

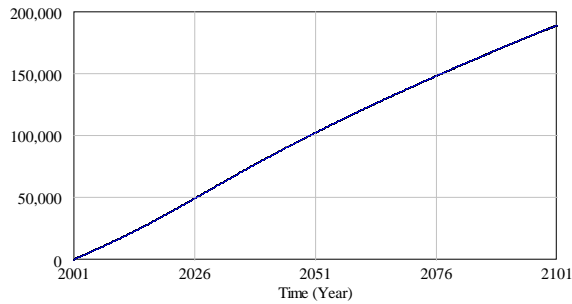


(g)

**Figure 7-20. Sensitivity Results for Average Years to Develop Early Stage
Complication from Diagnosed Diabetes and Mortality Rate of Diagnosed Diabetes
without Complication**

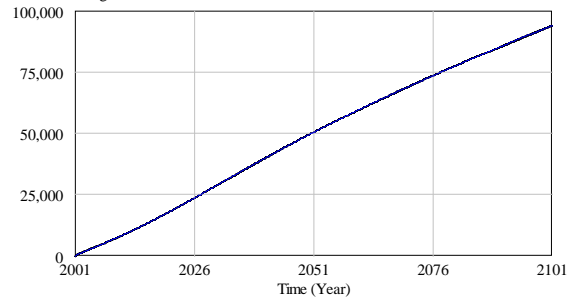
The combination of changes to the *average years to develop early stage complication from diagnosed diabetes* and the *mortality rate of diagnosed diabetes without complication* has its focus on the diabetic population. It does not exert a direct impact on the diabetes incidence; hence, the sensitivity levels for the outcome variables that relate to diabetes incidence are not high, as shown in Figure 7-20a, 7-20b and 7-20g. The changes in this variable combination have direct impacts on the diagnosed diabetic without complication population and the diagnosed diabetic with early stage macrovascular complication population, but the levels of impacts are not obvious due the small population base. The changes also have a direct impact on the death of diabetics, but the impact level is limited as shown in Figure 7-20e.

v3-28 Mortality for Dx Diab with Early Comp + Mortality for Dx Diab with Late Comp Coeffix
Cumulative incidence of diabetes



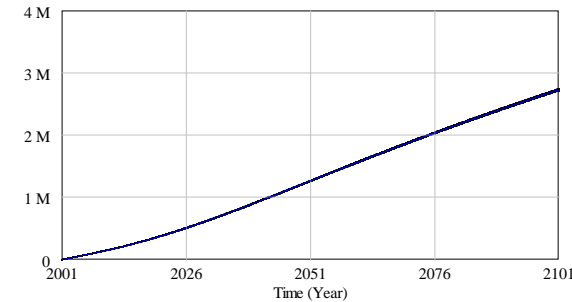
(a)

v3-28 Mortality for Dx Diab with Early Comp + Mortality for Dx Diab with Late Comp Coeffix
Cumulative diagnosed incidence of diabetes



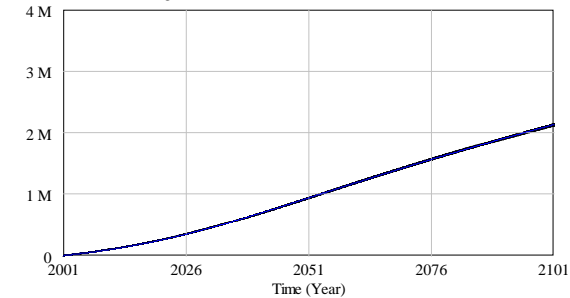
(b)

v3-28 Mortality for Dx Diab with Early Comp + Mortality for Dx Diab with Late Comp Coeffix
Cumulative number of diabetic



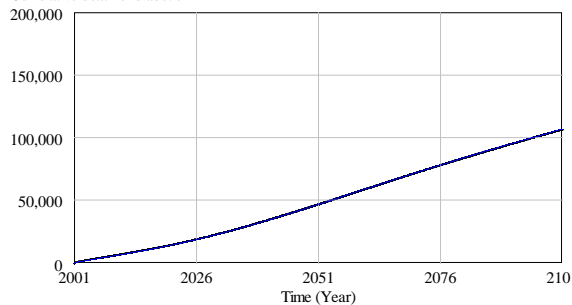
(c)

v3-28 Mortality for Dx Diab with Early Comp + Mortality for Dx Diab with Late Comp Coeffix
Cumulative number of diagnosed diabetic



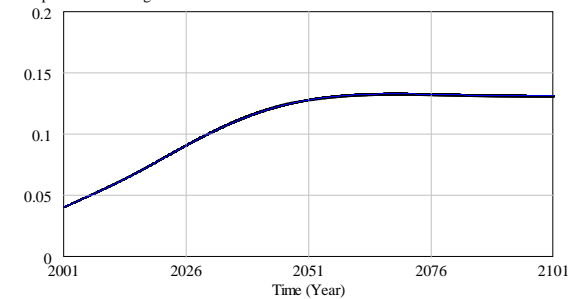
(d)

v3-28 Mortality for Dx Diab with Early Comp + Mortality for Dx Diab with Late Comp Coeffix
Cumulative death of diabetic

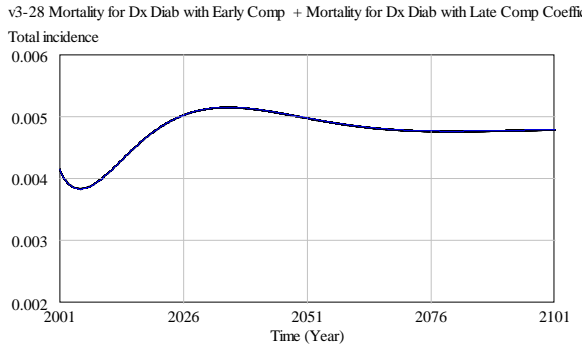


(e)

v3-28 Mortality for Dx Diab with Early Comp + Mortality for Dx Diab with Late Comp Coeffix
total prevalence of diagnosed diabetes



(f)

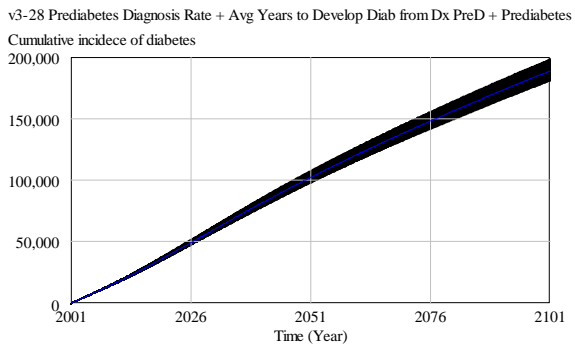


(g)

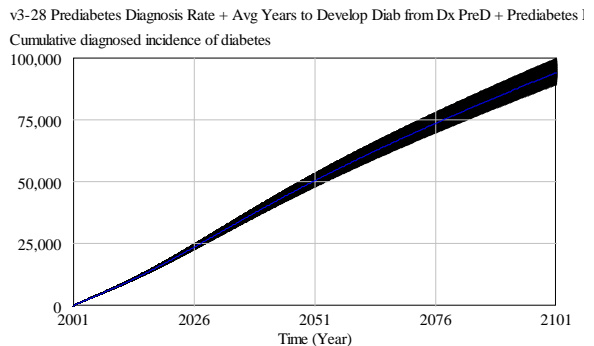
Figure 7-21. Sensitivity Results for Mortality Rate of Diagnosed Diabetes with Early Stage Complication and Mortality Rate of Diagnosed Diabetes with Late Stage Complication

The combination of changes to the *mortality rate of diagnosed diabetes with early stage complication* and the *mortality rate of diagnosed diabetes with late stage complication* directly targets the mortality rates of diabetic patients. The changes in this variable combination have no direct impacts on diabetes incidence and diabetes prevalence. Figure 7-21a and 7-21b show the *cumulative diabetes incidence* and the *cumulative diagnosed diabetes incidence* exhibit little response to simultaneous changes in the variable combination.

Changes in mortality rates have direct impacts on the diabetic population and the death of diabetics, but the impacts are weakened on the *cumulative number of diabetic*, *cumulative number of diagnosed diabetic* and *cumulative death of diabetes* due to the small population base in the *diagnosed diabetic with early stage macrovascular complication* and the *diagnosed diabetic with late stage macrovascular complication* population groups. These result variables only exhibit very small levels of variance as shown in Figure 7-21c, 7-21d and 7-21e.



(a)



(b)

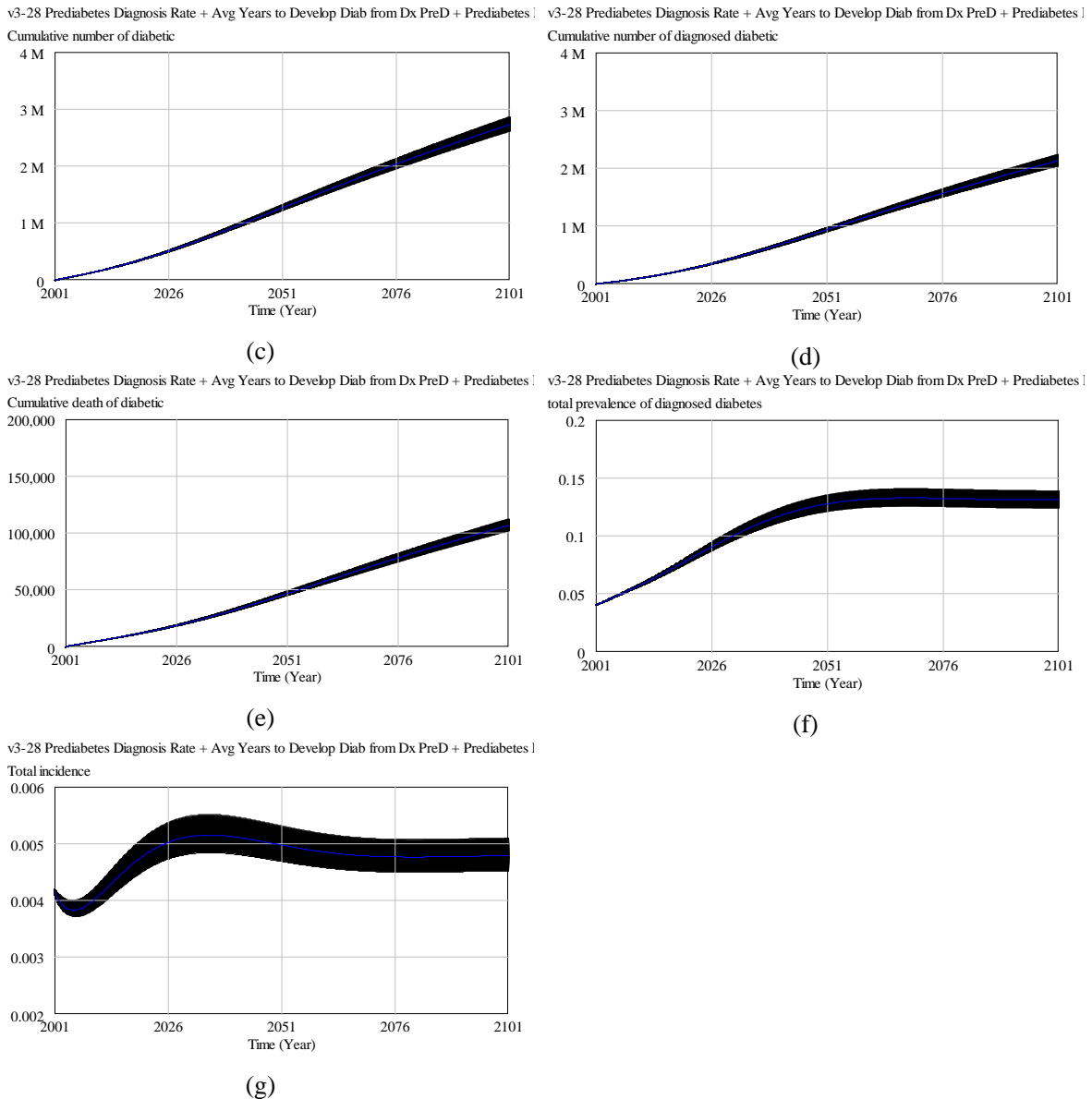


Figure 7-22. Sensitivity Results for Prediabetes Diagnosis Rate, Prediabetes Recovery Rate and the Average Years to Develop Diabetes from Diagnosed Prediabetes

Figure 7-22 illustrates sensitivity results for simultaneous changes to the combination of the *prediabetes diagnosis rate*, the *prediabetes recovery rate* and the *average years to develop diabetes from diagnosed prediabetes*. This variable combination has its focus on the diagnosed prediabetic population. The changes in the *prediabetes diagnosis rate* and the *prediabetes recovery rate* directly impact the diagnosed prediabetes population and further affect the incidence of diabetes and the prevalence of diabetes. *Average years to develop diabetes from diagnosed prediabetes* controls the incidence of diabetes from the diagnosed prediabetic population. The

changes in the *average years to develop diabetes from diagnosed prediabetes* have impacts on the incidence of diabetes and the prevalence of diabetes. Therefore, the changes in these three test parameters significantly affect all cumulative and non-cumulative result variables. The *cumulative incidence of diabetes*, *cumulative incidence of diagnosed diabetes* and *total incidence* are especially sensitive to the changes in the variable combination since all three test parameters have impacts on the incidence of diabetes.

In the multi-variable sensitivity analysis, we tested several variable combinations, which have the potential to be modified by common intervention policies. From the results, we can see that some variable combinations have greater impacts on the diabetes burden than others. For instance, the combination of the *average years to develop diabetes from diagnosed prediabetes* and the *average years to develop diabetes from undiagnosed prediabetes* has heavy impacts on the diabetes population, but the combination of the *mortality rate of diagnosed diabetes with early stage complication* and the *mortality rate of diagnosed diabetes with late stage complication* has very light impacts on the diabetes population. In the next section, I am going to discuss possible interventions based on the sensitivity analysis.

7.2 Potential Interventions

The results from the sensitivity analysis show that the simulated diabetes burden - such as the diabetes incidence and the diabetes prevalence - can be changed greatly if we alter certain parameters in the model. This raises the potential of lowering the diabetes prevalence, diabetes incidence rate and other diabetes burden in the SHR if we can change some conditions in the current system. Based on what we observed in the sensitivity analysis, several potential types interventions merit comment.

7.2.1 Interventions for Normoglycemic Population

As discussed in the previous section, the parameter combination of *overweight incidence rate* and *obese incidence rate* has a significant impact on the diabetic population. Intervention policies based on lowering the overweight incidence rate and the obesity incidence rate - such as fitness classes, support for recreational facilities, and programs to make nutritious food more affordable and accessible when compared with less nutritious food, can help to lower the diabetes prevalence and diabetes incidence rate in the long run, as shown in the Figure 7-23. The projections of diabetes prevalence and incidence rate given by lowering overweight incidence rate and obesity incidence rate by

fivefold, which are plotted by blue lines are lower than their the baseline projections. These intervention policies can lower the overweight incidence rate and the obesity incidence rate, and will slow down the rate at which the diabetic population and diabetes prevalence are rising, as well as the diabetes related burdens.

This kind of interventions will not lower the diabetic population from its original path immediately since they are not intervening directly on the diabetic population directly. The changes in the overweight and obese population will affect the diabetic population with levels of delays and manifest their impacts in the long run.

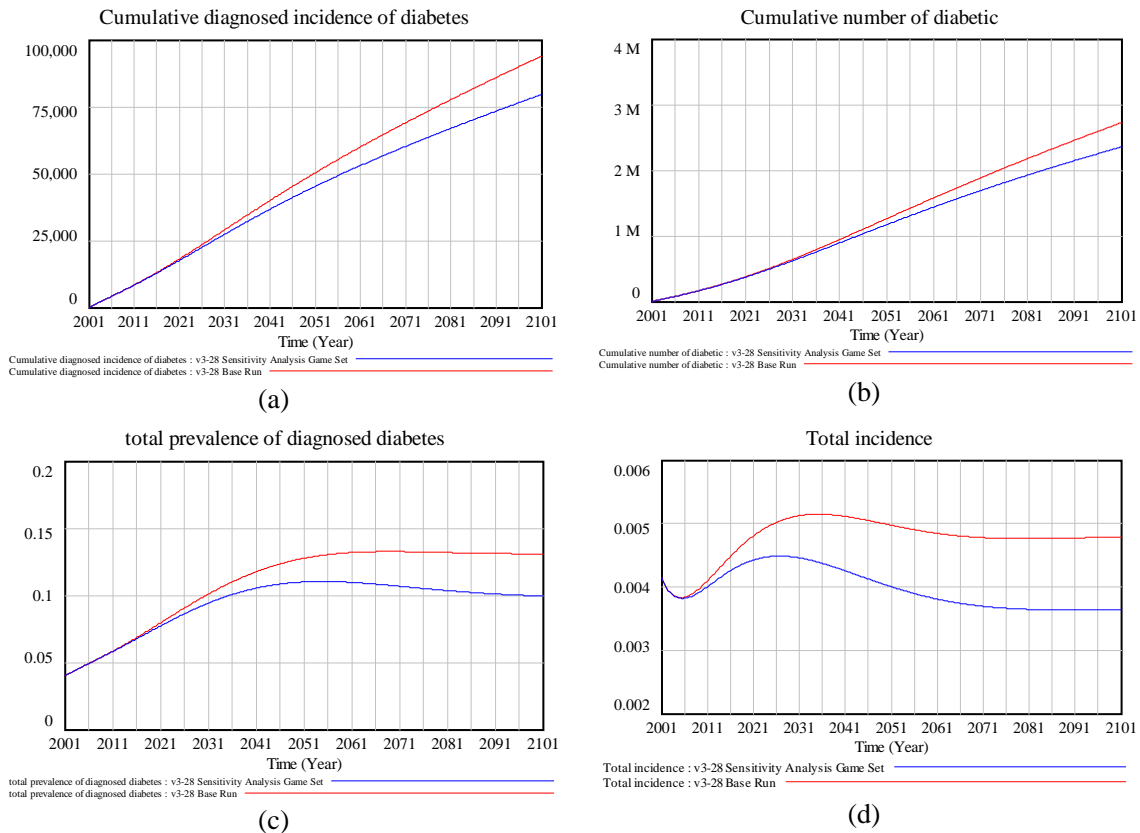


Figure 7-23. Changes in Diabetes Burdens from Lowering Overweight Incidence Rate and Obese Incidence Rate Fivefold

7.2.2 Interventions Involving the Hyperglycemic Population

In the sensitivity analysis, we tested several variable combinations that focus on the hyperglycemic population. These variable combinations have impacts on the prediabetic population and all stages of the diabetic population. The parameter combination of *average years to develop diabetes from undiagnosed prediabetes* and *average years to develop diabetes from diagnosed prediabetes* is one of these

combinations. Intervention policies such as nutrition and diet education for prediabetic population, physical activity programs for high risk groups and frequent screening program for high risk population groups could be employed for the purpose of delaying progression time from prediabetes to diabetes. The sensitivity analysis results in Figure 7-18 suggest that the diabetes population is very sensitive to the changes in this parameter combination. If we implement an intervention policy to delay diabetes onset in the prediabetic population, it could greatly lower diabetes incidence and the diabetes prevalence greatly. Figure 7-24 illustrates the improvement in the diabetes prevalence and the number of new incident cases by doubling the *average years to develop diabetes from undiagnosed prediabetes* and the *average years to develop diabetes from diagnosed prediabetes*. The diabetes prevalence and incident of new cases (illustrated by blue lines) are much lower than the baseline.

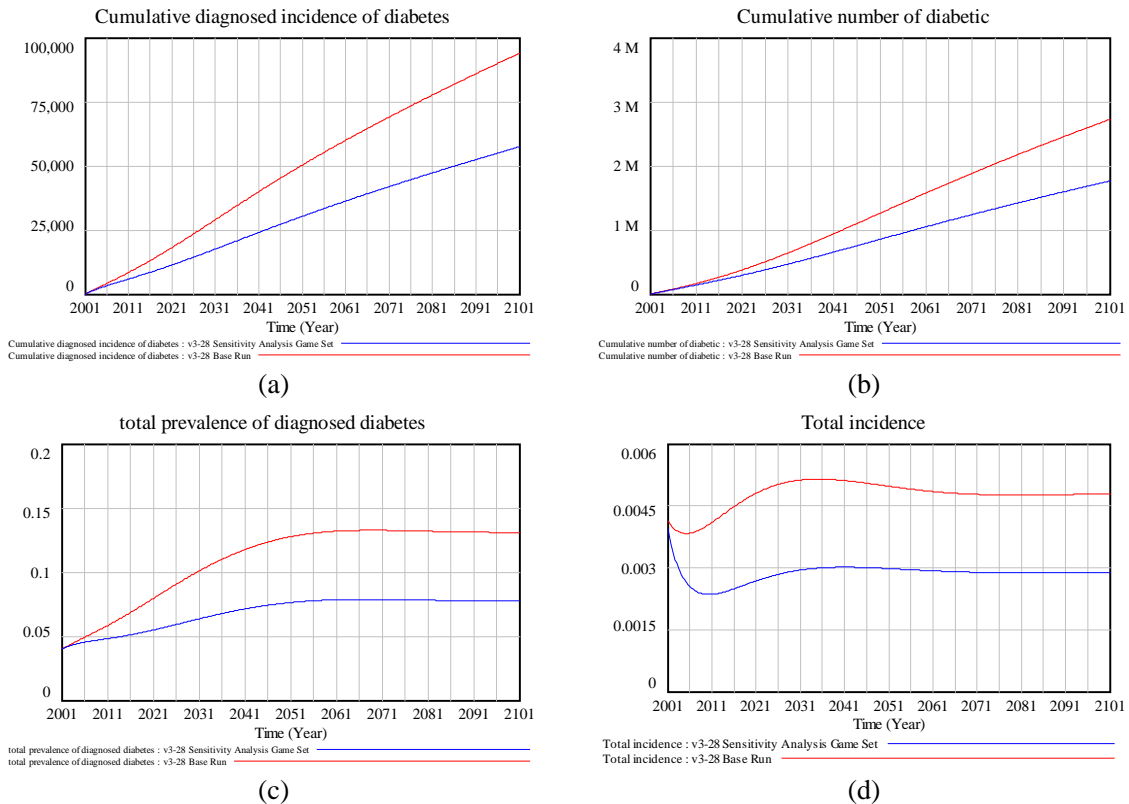
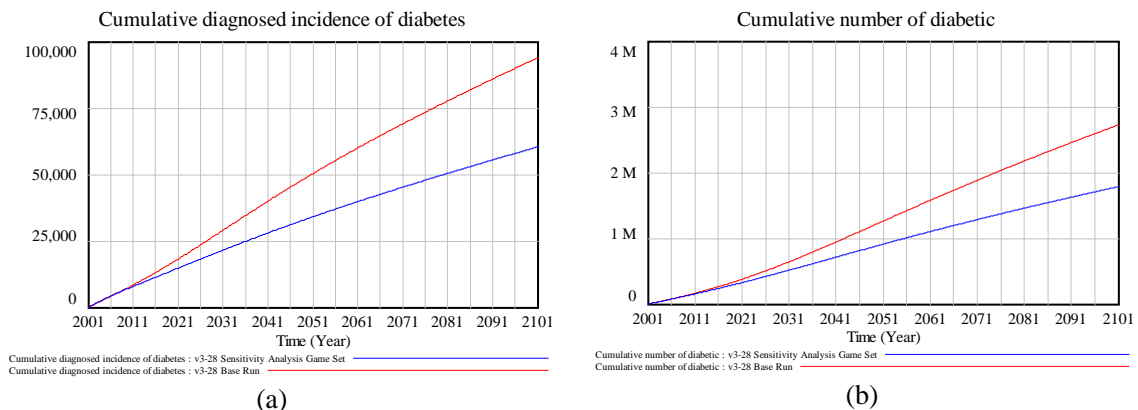


Figure 7-24. Changes in Diabetes Burdens from Doubling Average Years to Develop Diabetes from Diagnosed Prediabetes and Undiagnosed Prediabetes

The sensitivity results for changing the parameter combination of *developing prediabetes from obese population incidence rate* and *prediabetes diagnosed rate* show that monitoring for high risk population groups can be an effective intervention policy.

Decreasing the *developing prediabetes from obese population incidence rate* could lower the prediabetes population and further reduce the diabetic population. Increasing the *prediabetes diagnosis rate* could temporarily increase the diagnosed prediabetic population – reflecting the short-term increase individuals being diagnosed – but it will lower the diabetic population in the long run since the diagnosed prediabetic population has a lower risk of developing diabetes than the undiagnosed prediabetic population. The combination of decreasing the *developing prediabetes from obese population incidence rate* and increasing the *prediabetes diagnosis rate* can help to greatly lower the incidence of diabetes and the prevalence of diabetes. Intervention policies such as blood glucose level monitoring programs and weight control programs (including different balances of physical activity and nutrition) for obese population could aid in lowering the *developing prediabetes from obese population incidence rate* and raising the *prediabetes diagnosed rate*.

Figure 7-25 illustrates the changes in several important diabetes burden indicators that result from lowering the *developing prediabetes from obese population incidence rate* by a factor of five and raising the *prediabetes diagnosed rate* by a factor of five. The projection of the *cumulative diagnosed incidence of diabetes*, the *cumulative number of diabetic* and the *total prevalence of diagnosed diabetes* resulting from the intervention – which are plotted by the blue lines – are lower than their original baseline path (plotted by the red lines). The *total incidence* projection associated with the intervention is slightly higher than the original path for a short time period at the beginning of the simulation, as shown in Figure 7-25d. The increase in the *total incidence* results from the rising in prediabetes diagnosed rate. After a brief period, the total incidence rapidly decreases, both in absolute terms, and when compared to the baseline.



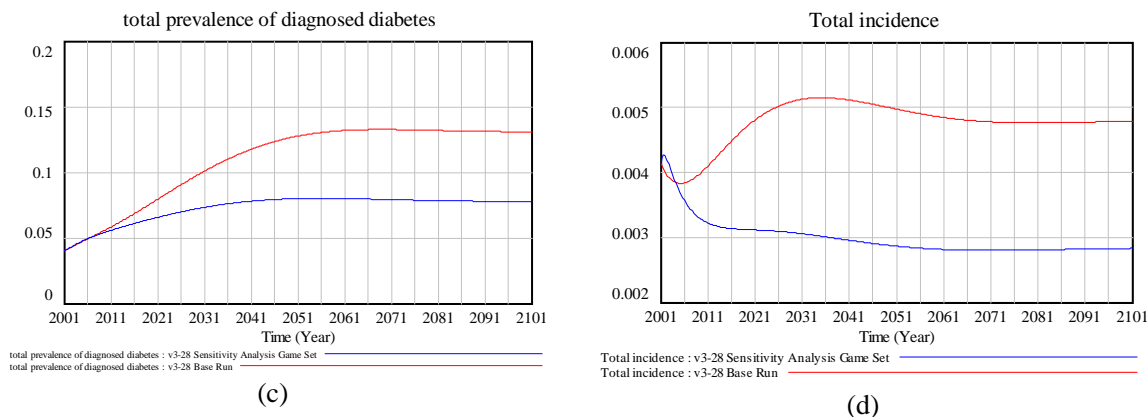


Figure 7-25. Changes in Diabetes Burdens from Lowering Developing Prediabetes from Obese Population Incidence Rate Fivefold and Rising Prediabetes Diagnosis Rate Fivefold

7.2.3 Discussion

Sensitivity analysis provides intuitive evidence that changes in model parameters can trigger changes in model results. The diabetes burdens – such as the prevalence of diabetes and the incidence of diabetes – are sensitive to changes in some conditions. By implementing intervention policies that alter these conditions, we can greatly lower the burden of diabetes.

Moreover, the sensitivity analysis results suggest that the overall diabetes burden examined here are not sensitive to the changes in some other conditions. For example, the changes in the *mortality of diagnosed diabetes with early stage complication* and the *mortality of diagnosed diabetes with late stage complication* do not have large impacts on the important indicators of diabetes burden discussed here. However, that these conditions do not have large impacts on the overall diabetes burdens does not mean they are insignificant. Specifically targeted intervention policies, which implement changes in these insensitive conditions, still greatly help lowering the diabetes burden in special areas. For instance, if the health care system can provide a better treatment for diabetic with complications, it would lower the *mortality of diagnosed diabetes with early stage complication* and the *mortality of diagnosed diabetes with late stage complication*. This intervention can save many diabetic patients' lives even though it has no help on lowering the diabetes prevalence and the diabetes incidence.

Intervention experiments show the possibility of reductions in the burden of diabetes. Changes in certain conditions from the *status quo* could yield great improvements on the burden of diabetes. However, our model does not capture inputs

requirement necessary for implementation of the interventions. Some intervention policies can have significant improvements on the diabetes burdens, but they may require huge amount of capital, human resources and careful coordination to achieve. Some intervention policies may only have certain levels of improvements, but they are relatively inexpensive to implement. Moreover, my thesis does not compare the tradeoff within and between intervention policies, for example in the form of transfer effects. An intervention policy could save more lives in one population group but raise the risk of death for another population group, or saves life but lower quality of life at the same time. These features lie outside the scope of my research, but they can be added into the model in the future.

7.3 Summary

Sensitivity analysis shows the behavior of the simulated system when changing certain conditions in the system. In this analysis process, I changed the value of single or multiple test parameters to 80%, 85%, 90%, 95%, 105%, 110%, 115% and 120% from their original values, and observed the changes in selected outcome variables.

The test parameters are variables selected to initialize the change in this process. The selection of the test parameters covers three broad areas: hyperglycemia diagnosis rates, progress rates and mortality rates for different population groups. The hyperglycemia diagnosis rates test parameters include the *prediabetes diagnosis rate* and the *diabetes diagnosis rate*. The test parameters that belong to the hyperglycemia progress rates are the *overweight incidence rate*, the *obesity incidence rate*, the *developing prediabetes from obese population incidence rate*, the *prediabetes recovery rate*, the *average years to develop diabetes from undiagnosed prediabetes*, the *average years to develop diabetes from diagnosed prediabetes*, the *average years to develop early stage complication from undiagnosed diabetes* and the *average years to develop early stage complication from diagnosed diabetes*. The mortality rates test variables are the *mortality rate of diagnosed prediabetes*, the *mortality rate of diagnosed diabetes without complication*, the *mortality rate of diagnosed diabetes with early stage complication* and the *mortality rate of diagnosed diabetes with late stage complication*.

The outcome variables are defined in the system in order to observe and compare levels of changes from the sensitivity test. The outcome variables are important indicators for diabetes burdens as well. There are seven outcome variables I defined in the system; they are the *cumulative incidence of diabetes*, the *cumulative diagnosed incidence of*

diabetes, the *cumulative number of diabetic*, the *cumulative number of diagnosed diabetic*, the *cumulative death of diabetic*, the *total prevalence of diagnosed diabetes* and *the total incidence of diabetes*.

I performed single parameter sensitivity testing as the first step. In this step, I altered one test parameter while holding other test parameters constant. Any change in the system is influenced by the altered test parameter. The sensitivity analysis shows that most outcome variables are not very sensitive to the changes in the hyperglycemia diagnosis rates. The *cumulative number of diabetic* is relatively less sensitive to the changes in the hyperglycemia diagnosis rates since diagnosis does not change the status of having diabetes. The *cumulative death of diabetic* is also less sensitive to changes in the hyperglycemia diagnosis rates.

The outcome variables are quite sensitive to changes in the upstream hyperglycemia progress rates. The changes in the *overweight incidence rate*, the *obesity incidence rate*, the *developing prediabetes from obese population incidence rate*, the *average years to develop diabetes from undiagnosed prediabetes* and the *average years to develop diabetes from diagnosed prediabetes* lead to relatively high impacts on the diabetes incidence and the number of diabetic population. The impacts on the diabetic population lead to further changes in the diabetes prevalence and the number of deaths per year of diabetics. The *prediabetes recovery rate* is an exception in the upstream hyperglycemia progress rates. The outcome variables are relatively insensitive to the changes in the *prediabetes recovery rate* due to the small original value involved.

Compared to the upstream progress rates, the downstream hyperglycemia progress rates have lower levels of impacts on the selected outcome variables. The changes in the *average years to develop early stage complication from undiagnosed diabetes* lead to mild levels of changes in the underlying diabetes incidence since the development of complications is a path of diagnosis according our definition. The levels of impacts are even lower on other result variables. The chosen outcome variables are insensitive to the changes in the *average years to develop early stage complication from diagnosed diabetes* as well.

The selected outcome variables are also very insensitive to the changes in mortality rates. The changes in the *mortality rate of diagnosed prediabetes*, the *mortality rate of diagnosed diabetic without complication*, the *mortality rate of diagnosed diabetic with early stage complication* and the *mortality rate of diagnosed diabetic with*

late stage complication have very low levels of impacts due to the small original values and the small population bases, but also to the fact that the mortality rates do not have direct impact on the selected outcome variables.

After the single variable sensitivity analysis, I performed multi-variable sensitivity analysis. In this step, I grouped two or more test parameters based on their focus areas and altered values of test variables together within the group. All parameter combinations and their focus areas are listed in Table 7-1. Generally, the sensitivity levels for parameter combinations are higher than the sensitivity levels for each individual test parameter in the combination, but lower than the sum of the sensitivity levels for individual test parameter.

Following sensitivity analysis, I proposed several intervention experiments that try to lower the diabetes burdens in the model based on observations from the sensitivity analysis. If the outcome variables, which are the important indicators of diabetes burdens, are sensitive to the changes, then the likelihood of lowering diabetes burdens is higher when other conditions hold. Hence, the intervention experiments I conducted are as follows: 1) lowering the overweight incidence rate and the obesity incidence rate, 2) increasing the average years to develop diabetes from diagnosed prediabetes and undiagnosed prediabetes (retard the onset of diabetes for diagnosed and undiagnosed prediabetics), and 3) lowering the development of prediabetes from the obese population incidence rate and elevating the prediabetes diagnosis rate. The results suggest that the major diabetes burdens can be lowered by the intervention policies.

The calibration process and the model results show that the model simulates the diabetes burdens in the SHR with acceptable fidelity. The model is able to reproduce the historical trace of diabetes burdens in the SHR and project the reasonable trend of the diabetes burdens based on available information. The sensitivity analysis and the intervention experiments suggest significant opportunities for lowering the diabetes prevalence and the diabetes incidence rate in the SHR. In conclusion, we believe that the model can be a very useful tool to help the decision makers examine and improve potential interventions. In the next and the final chapter, we are going to review our study and conclusion.

CHAPTER 8

CONCLUSION

There is no doubt about burdens imposed by Type 2 diabetes in the SHR. With increase in the prevalence of obese population, the prevalence of Type 2 diabetes also rapidly increased in the SHR. In this thesis, we sought to build a System Dynamics simulation model that represents the Type 2 diabetes situation in the SHR. The simulation model provides a good tool for gaining understanding on the reasons underlying high diabetes prevalence. The model is also a useful tool to assist users to test potential interventions.

In this chapter, I am going to review and summarize the process for constructing the simulation model, the calibration process after the model is created and the observations from the simulation results. I will highlight some unique features of my study. I also will briefly outline future research directions.

8.1 Thesis Summary

8.1.1 Model Construction

For this thesis, I constructed a simulation model for the diabetes in the SHR using a System Dynamics approach. The model uses population stocks and flows to simulate the dynamics in the Diabetes situation in the SHR.

The model contains two core sections: the normoglycemic population section and the hyperglycemic population section. I adapted the structure of the normoglycemic population from the New Zealand model [51], correcting for some important misformulations in that model and adding additional details. As its name suggests, the normoglycemic population section represents the population that does not have hyperglycemia but has the risk of developing hyperglycemia. The normoglycemic population section in my model is divided into three main subgroups: the normal weight population, the overweight population and the obese population. Different weight subgroups have different levels of risks of developing hyperglycemia. Individuals with heavier weights generally have a higher risk of developing hyperglycemia.

The population in each main subgroup is further divided into small scale subgroups according age, ethnicity and gender in my model. The population is disaggregated into 5-year age categories up to age 79; all of the population older than 80 (of a given ethnicity and gender group) forms another age group. All age subgroups within a given weight group form an aging

chain together since every year some population flows to the next age group as they age. The model in [51] does not disaggregate the diabetic population according to age, which in some cases causes misleading results.

The population flows into the hyperglycemic population section once they develop any hyperglycemic condition. The structure of the hyperglycemic population section was adapted from the CDC model [49], with addition of many details. The hyperglycemic population section is divided into 4 hyperglycemia progression stages: the prediabetes stage, the diabetes without complication stage, the diabetes with early stage macrovascular complication stage and the diabetes with late stage macrovascular complication stage. Population in each progression stage is further separated into two components: the undiagnosed population and the diagnosed population, except for individuals with the diabetes with late stage macrovascular complication stage. The hyperglycemic population, starts from the undiagnosed prediabetes group, moves to the next stage if the hyperglycemia condition becomes worse, or moves to the corresponding diagnosed group once the undiagnosed condition is diagnosed. Like population groups in the normoglycemic population section, population groups in the hyperglycemic population section are further divided into small scale subgroups by age, ethnicity and gender.

8.1.2 Model Calibration

After the model is constructed, I parameterize the model using local diabetes data. I was able to find data sources and parameterize most parameters in the model. However, I was unable to locate reliable data for some model parameters. Hence, I used calibration technique to estimate or interpolate the values of these unknown parameters from indirect or aggregate data sources. The calibration software alters the unknown parameters within reasonable regions and the model outputs different results. The software compares the model results with aggregate historical data. The values of unknown parameters, which produce the best match result against historical data, are considered the best estimated values.

I also verified the existing model data and examined the model structure through the calibration process. By back tracing the disagreements between the existing model data and the historical data, I was able to identify issues in the existing model data, equations and structures, and fine tune the model.

8.1.3 Model Results

After the model is examined and fine tuned through the calibration process, I used the

model to project the diabetes prevalence and incidence over the mid-term future based on current conditions. The simulation results show that the obese populations rapidly increases and reaches its peak value around the year 2026. The prediabetic and diabetic populations also increase with the obese population. The prediabetic population reaches its peak value around the year 2031 and the diabetic population will reach the peak value around the year 2051. After the obese, prediabetic and diabetic populations reach the peak values, they slowly decrease.

The simulated prevalence of diabetes in the SHR steady climbs in the first half of 100-years simulation period for both male and female of the non-RI population. The acceleration of the prevalence slows down in the second half of the simulation period. The simulation results exhibit the steady climb in prevalence for the RI population during the first half of the simulation period. However, diabetes prevalence slowly decreases after the year 2061 for both male and female of the RI population. This decrease I believe is due to decrease in the normoglycemic population and the young age structure in the RI population since the simulation results are not age standardized.

The simulation results show that the number of incident new cases of diabetes quickly decreases in the first 5-year period. This decrease is caused by inconsistency between initial values and estimated transition rate. After the impact of the initial values fade out, the number of incident cases of diabetes occurring per year increase rapidly. The increase in the total number of diabetes incident cases rises continuously until the year 2031, then it starts to drop slowly. The number of diabetes incident cases in the RI population has a longer increase time period than the total number of incident cases cross all ethnic groups. The number of annual diabetes incident cases of the RI population increases until the years 2041 and decreases afterwards.

8.1.4 Sensitivity Analysis and Interventions

I performed sensitivity analysis of selected model parameters to understand the possible levels of impacts from these chosen model parameters. By altering the value of each such parameter to 80%, 85%, 90%, 95%, 105%, 110%, 115% and 120% from its baseline value, I observed the changes in several outcome variables. The outcome variables are selected key indicators for the burden of diabetes in SHR, such as the cumulative diabetes prevalence, the cumulative diabetes incident cases and the cumulative deaths by diabetics. By observing the changes in the outcome variables, we gained some good understandings on the levels of impacts of the diabetes prevalence and diabetes incidence from the differences of the model parameters.

From the observations, the outcome variables are not very sensitive to the prediabetes and diabetes diagnosis rates. Nevertheless, the outcome variables are quite sensitive to the changes in the upstream progress rates, such as the *overweight incidence rate*, the *obesity incidence rate*, the *developing prediabetes from obese population incidence rate*, the *average years to develop diabetes from undiagnosed prediabetes* and the *average years to develop diabetes from diagnosed prediabetes*. The downstream progress rates, such as the *average years to develop early stage complication from undiagnosed diabetes* and the *average years to develop early stage complication from diagnosed diabetes*, lead to lower level of impacts on the outcome variables than on the upstream progress rates.

After having done a single-variable sensitivity analysis, I performed multi-variable sensitivity analysis. I grouped two or more test model parameters, which likely can be altered by one intervention policy, and independently altered their values to 80%, 85%, 90%, 95%, 105%, 110%, 115% and 120% from the baseline values. From our observation, the sensitivity levels for parameter combinations are higher than the sensitivity levels for each individual parameter in the combination, but lower than the sum of the sensitivity levels for individual parameters.

Based on our observations from the sensitivity analysis, I proposed several interventions. The projections of diabetes prevalence and incidence resulting from the interventions are lower than in the baseline projection.

8.2 Contributions

My simulation model is built on a foundation of pioneering research, but it also has many unique features that do not appear in other research efforts. First, my model is characterized with the unique demographic structure in the Saskatoon Health Region. The initial values of the population stocks are filled with demographic data specific to that context. Secondly, the model is also distinguished by a finely disaggregated population structure. The normoglycemic population in my model is disaggregated into subpopulation groups according to age, ethnicity, gender and weight status. The CDC model does not contain the same disaggregated population structure. The CDC model uses several risk factors (such as the risk multiplier for elderly and risk multiplier for obese) to represent different levels of risk of developing Type 2 diabetes in different subpopulation groups. However, this structure can lead to artifacts in results for some subpopulation groups because the simple multiplication of risks implicitly assumes these risk factors are independent of each other. The hyperglycemic population in my model is

disaggregated into subpopulation groups according to age, ethnicity and gender. Although the New Zealand model contains some age and ethnicity structure in the normoglycemic population section, it does not disaggregate by age, ethnicity or gender in the hyperglycemic population section. As I described in chapter 4, my exploration with the model found that the lack of age structure in the hyperglycemic population section can cause significant artifacts in results. The population structure in my model can capture the distinct difference in demographic structure between the Aboriginal population and the non-Aboriginal population. This presence of disaggregated population structure can also highlight the fact that Type 2 diabetes is prevalent among elderly, Aboriginal female and non-Aboriginal male subpopulation groups.

Thirdly, my model includes a detailed diabetes and – to the best of my knowledge – unique progression structure. Starting from the prediabetes phase, progressing to diabetes without complication phase, to diabetes with early stage macrovascular complications phase, and ending at diabetes with late stage macrovascular complications phase, the diabetes progression structure distinguished different stages of diabetic population in different progression stages. After the consultation with an epidemiologist of the College of Medicine, University of Saskatchewan, I decided to use macrovascular complications as an important divide in diabetes progression since macrovascular complications are the main driving factors in diabetes-related deaths.

Fourth, many parameters values in my model are derived through systematic search and analysis of secondary data sources. In the cases where no local data was available, I estimated the parameters' values from related-data of other regions. In the cases in which there was no available data for the simulation period, I interpolated or “backed out” from the data for other time period. In the cases in which no disaggregated data was available, I disaggregated the data by interpolation or applying related ratios.

Finally, my model is intensively calibrated against other related data sources. The calibration process identified major structural defects in the model and estimated values of unknown parameters using constraints imposed by model structure and historic data. The calibration process was repeated several times after changes in model parameters or modification in model structure. I added a weighting structure for the calibration process. The weighting structure dynamically assigns different weight to different components based on their importance and with consideration of sampling errors and model errors. Robustness and integrity of the

model are improved to an acceptable level after several iterations of the calibration process.

8.3 Future Work

Although the simulation model is based on reasonable assumptions and the simulation results suggests the potential interventions with the aim of lowering diabetes prevalence and incidence, there is still a large space for improvements. There are also unsolved issues that merit further investigations.

First, I defined a range for the value of each parameter in my calibration list during the calibration process. The given range is either defined based on related research or on a reasonable guess. In some cases, the calibration process assigned a boundary value as the “best fit” value of some calibrated parameters. This suggests that the calibration process may find an even better match with historic data for values beyond the given range. However, a value beyond the given range appears to make the estimated value of the parameter unreasonable. I also tried to assign a value beyond the range to the parameter and observed the calibration payoff. The final payoff did not show a significant improvement. It is possible the software tried to match other components in the model and has to accept larger discrepancies for some light weighted components. Trying to find out why calibrated parameter values reach the given boundaries requires further investigation.

Second, my research was focused on the diabetes prevalence and incidence rates. There are many other important indicators for the burden imposed by diabetes beyond prevalence and incidence. For example, diabetic patients’ wellness can be measured using quality of life and diabetes related expenditure can be measured using dollar value. The measurement of quality of life is already built in the model but is not used. Other add-on components can be added into the model as well. Improvement on the other diabetes burden indicators constitutes one possible future research direction.

Third, representation of other diabetes related complications can be considered as an important future work. In my research, I used major macrovascular complications – such as AMI or stroke – to represent causes of dying from diabetes. There are many other complications that are not reflected in my model, like nephropathy and neuropathy. It will be important to incorporate these complications to improve the model in the future.

Finally, population migrations deserve future investigations. As one limitation of my model, we made a simplifying assumption that the net population migration for the SHR is zero.

However, this is not the case in reality. The total population is covered in SHRA experienced relatively high levels of out migration and in migration during the last decade. Without population migrations, the population counts – both for the normoglycemic population and the hyperglycemic population – in the model do not reflect the actual population size in the SHR. Hence, the model can be improved in accuracy if the population migration flows are added.

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APPENDIX A: STOCK INITIAL VALUES

Normal Weight General Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	778.81	664.48	4864	4482
5 - 9	572.51	567.95	4716	4442
10 - 14	559.66	556.97	5078	5038
15 - 19	320	398.36	3901	4392
20 - 24	340.55	441.88	3845	5414
25 - 29	176.31	301.98	2480	3754
30 - 34	144.64	259.9	1697	3026
35 - 39	94.54	165.43	2652	4227
40 - 44	56.62	112.49	1898	4418
45 - 49	15.06	40.54	1593	3522
50 - 54	16.46	40.26	1060	2262
55 - 59	11.85	13.46	716.59	1457
60 - 64	7.669	5.72	639.51	1160
65 - 69	5.61	4.659	544.31	1038
70 - 74	3.505	2.531	511.48	748.04
75 - 79	1.977	1.21	364.77	751.68
80 plus	0.7944	1.126	590.83	1842

Overweight General Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	128.02	151.12	562.94	703.42
5 - 9	207.43	233.37	1041	1138
10 - 14	185.23	162.15	1032	956.06
15 - 19	260.1	211.16	1997	1612
20 - 24	250.2	169.38	2612	1504
25 - 29	303.98	178.72	2756	1774
30 - 34	249.38	153.82	2954	1914
35 - 39	181.53	112.63	2939	1676
40 - 44	108.72	76.59	2952	1947
45 - 49	34.91	26.27	3069	1601
50 - 54	38.16	36.02	2554	1578
55 - 59	18.62	1795	1443	1152
60 - 64	12.05	7.627	746.09	1104
65 - 69	8.816	6.212	882.16	915.03
70 - 74	5.508	3.374	608.24	955.83
75 - 79	3.108	1.613	496.49	966.23
80 plus	1.248	1.501	484.48	889.28

Obese General Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	160.03	143.93	346.42	331.02
5 - 9	257.21	231.31	668.32	538.47
10 - 14	240.41	162.15	678.95	465.11
15 - 19	208.08	139.27	758.97	550.75
20 - 24	104.25	125.2	798.15	601.65
25 - 29	127.67	135.58	1653	1296
30 - 34	104.74	116.69	1634	1235
35 - 39	102.11	73.91	1577	1384
40 - 44	61.15	50.26	2179	1123
45 - 49	18.48	29.87	1239	1280
50 - 54	20.2	29.66	1205	1420
55 - 59	11.85	13.46	836.02	779.62
60 - 64	7.669	5.72	746.09	497.23
65 - 69	5.61	4.659	450.46	159.34
70 - 74	3.505	2.531	262.65	374.02
75 - 79	1.977	1.21	151.98	297.17
80 plus	0.7944	1.126	106.34	444.64

Undx Prediabetic Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	3.73	3.054	55.02	30.96
5 - 9	14.92	15.27	89.41	56.3
10 - 14	14.92	24.43	127.24	112.61
15 - 19	33.57	45.81	151.31	143.58
20 - 24	67.15	73.3	199.45	202.7
25 - 29	74.61	97.74	330.14	273.09
30 - 34	97	119.12	464.25	385.7
35 - 39	104.46	131.34	694.66	472.98
40 - 44	97	125.23	863.17	557.44
45 - 49	89.54	100.79	887.24	529.29
50 - 54	25.86	30.95	431.01	288.29
55 - 59	15.91	21.17	422.01	789.79
60 - 64	7.959	14.66	405.33	297.3
65 - 69	3.979	6.516	304.46	279.28
70 - 74	1.989	4.887	335.64	427.93
75 - 79	1.989	4.887	335.64	427.93
80 plus	1.989	4.887	335.64	427.93

Dx Prediabetic Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	0.4	0.4	6.4	4.4
5 - 9	1.6	2	10.4	8
10 - 14	1.6	3.2	14.8	16
15 - 19	3.6	6	17.6	20.4
20 - 24	7.2	9.6	23.2	28.8
25 - 29	8	12.8	38.4	38.8
30 - 34	10.4	15.6	54	54.8
35 - 39	11.2	17.2	80.8	67.2
40 - 44	10.4	16.4	100.4	79.2
45 - 49	9.6	13.2	103.2	75.2
50 - 54	5.2	7.6	94	76.8
55 - 59	3.2	5.2	96.4	77.2
60 - 64	1.6	3.6	88.4	79.2
65 - 69	0.8	1.6	66.4	74.4
70 - 74	0.4	1.2	73.2	114
75 - 79	0.4	1.2	73.2	114
80 plus	0.4	1.2	73.2	114

Undx Diabetic without Complication Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	0	0	3.803	3.54
5 - 9	2.314	1.077	19.01	10.62
10 - 14	1.157	1.077	30.43	19.47
15 - 19	4.628	5.385	49.45	35.4
20 - 24	4.628	8.616	70.37	70.81
25 - 29	10.41	16.15	83.68	90.28
30 - 34	20.82	25.82	110.31	127.46
35 - 39	23.14	34.46	182.58	171.72
40 - 44	30.08	42	256.76	242.54
45 - 49	32.4	46.31	384.19	297.42
50 - 54	20.09	29.49	318.88	234.15
55 - 59	18.55	23.74	327.78	222.32
60 - 64	10.04	13.67	298.59	227.05
65 - 69	6.183	9.353	306.18	228.24
70 - 74	3.091	6.475	280.77	234.15
75 - 79	1.545	2.878	210.89	219.96
80 plus	0.7729	2.158	232.49	337.03

Dx Diabetic without Complication Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	0	0	2	2
5 - 9	2	1	10	6
10 - 14	1	1	16	11
15 - 19	4	5	26	20
20 - 24	4	8	37	40
25 - 29	9	15	44	51
30 - 34	18	24	58	72
35 - 39	20	32	96	97
40 - 44	26	39	135	137
45 - 49	28	43	202	168
50 - 54	26	41	251	198
55 - 59	24	33	258	188
60 - 64	13	19	235	192
65 - 69	8	13	241	193
70 - 74	4	9	221	198
75 - 79	2	4	166	186
80 plus	1	3	183	285

Undx Diabetic with Early Stage Complication Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	0	0	0	0
5 - 9	0	0	0	0
10 - 14	0	0	0	0
15 - 19	0	0	0	0
20 - 24	0	0	0	0
25 - 29	0	0	0	0
30 - 34	0	0	0	0
35 - 39	0	0	0	0
40 - 44	0	0	0	0
45 - 49	0	0	0	0
50 - 54	0	0	0	0
55 - 59	0	0	0	0
60 - 64	0	0	0	0
65 - 69	0	0	0	0
70 - 74	0	0	0	0
75 - 79	0	0	0	0
80 plus	0	0	0	0

Dx Diabetic with Early Stage Complication Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	0	0	0	0
5 - 9	0	0	2.991	1.994
10 - 14	0	0	4.985	3.988
15 - 19	1	1	6.979	5.982
20 - 24	1	2	8.973	9.97
25 - 29	2	4	11.96	13.95
30 - 34	5	7	16.94	20.93
35 - 39	7	11	31.9	31.9
40 - 44	10	15	49.85	50.84
45 - 49	8	19	60.81	72.78
50 - 54	11	21	104.98	99.98
55 - 59	1	21	8	188.98
60 - 64	7	7	127.98	67
65 - 69	4	7	117.98	105.98
70 - 74	3	7	151.98	149.98
75 - 79	1	5	102.98	215.97
80 plus	1	4	197.98	207.96

Dx Diabetic with Late Stage Complication Population

Age Groups	RI		Non-RI	
	male	female	male	female
0 - 4	0	0	0	0
5 - 9	0	0	0	0
10 - 14	0	0	0	0
15 - 19	0	0	0	0
20 - 24	0	0	0	0
25 - 29	0	0	0	0
30 - 34	0	0	0	0
35 - 39	0	0	0	0
40 - 44	0	0	0	0
45 - 49	4	0	28	0
50 - 54	2	0	21	0
55 - 59	14	0	155	0
60 - 64	3	8	57	83
65 - 69	4	5	115	81
70 - 74	2	4	110	85
75 - 79	2	1	142	58
80 plus	1	3	142	221

APPENDIX B: MODEL PARAMETER VALUES

Avg years to develop diabetes from undx prediabetes=10

Avg years to develop early stage complications from undx diabetes=10

Avg. HRQoL for dx diabetic with early stage
complication[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for dx diabetic with end stage
complication[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for dx diabetic without complication[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for dx prediabetic[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for normal weight general population[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for obese general population[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for overweight general population[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for undx diabetic with early stage
complication[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for undx diabetic without
complication[AgeGroups,EthnicGroups,GenderGroups]=1

Avg. HRQoL for undx prediabetic[AgeGroups,EthnicGroups,GenderGroups]=1

Base time between screenings for high risk asymptomatic population=2

Birth rate switch=1

Controlled birth rate[EthnicGroups,Female]=0

Controlled birth rate[EthnicGroups,Male]=0

Diabetic mortality from SHR report[AgeGroups,Aboriginal,Female]=0,-
0.0455556,0.0666667,0.00808081,0.0364331,0.0467909,0.011738,0.0139332,-

0.000276298,0.0099266,0.0109431,0.0134912,0.0238086,0.0383159,0.0584447,0.0904008,0.1781

Diabetic mortality from SHR report[AgeGroups,Aboriginal,Male]=0,-0.0382022,0.0932735,-0.0324324,0.0681818,0.051134,0.0135955,0.0166545,0.00648148,0.00535753,0.0159701,0.0132609,0.0393896,0.0555597,0.0727832,0.102645,0.3572

Diabetic mortality from SHR report[AgeGroups,Other,Female]=0,0.0332657,0.0364978,0.0260896,0.0228911,0.0348223,0.0307011,0.0311824,0.0185299,0.0175289,0.0234839,0.0147463,0.0302566,0.0265915,0.0319387,0.0396357,0.1781

Diabetic mortality from SHR report[AgeGroups,Other,Male]=0,0.0240927,0.0265,0.00961232,0.0197951,0.0434004,0.0461718,0.0358142,0.0355981,0.0271993,0.0229399,0.0181048,0.0324111,0.035572,0.0421769,0.0630917,0.3572

Diabetic mortality switcher=1

Dx diabetes progress coefficient=1.5

Dx diabetic complication progress coefficient=1.5

Dx prediabetic mortality switch=1

early stage complication diagnosis elderly coefficient=0.5

early stage complication diagnosis ethnic coefficient[Aboriginal]=0.9

early stage complication diagnosis ethnic coefficient[Other]=0.9

early stage complication diagnosis gender coefficient[Female]=0.9

early stage complication diagnosis gender coefficient[Male]=0.9

early stage complication diagnosis youth coefficient=0

First-ever AMI

mortality[AgeGroups,Female]=0,0,0,0,0.03,0.03,0.03,0.03,0.03,0.03,0.059,0.059,0.059,0.126,0.126,0.238,0.238

First-ever AMI

mortality[AgeGroups,Male]=0,0,0,0,0.014,0.014,0.014,0.014,0.014,0.014,0.038,0.038,0.038,0.094,0.094,0.22,0.22

First-ever AMI onset rate for diabetic

population[AgeGroups,Female]=0,0,0,0,0.0065,0.0065,0.0065,0.0343,0.0343,0.0343,0.0943,0.0943,0.1379,0.1379,0.1986,0.1986

First-ever AMI onset rate for diabetic

population[AgeGroups,Male]=0,0,0,0,0.0065,0.0065,0.0065,0.0343,0.0343,0.0343,0.0943,0.0943,0.1379,0.1379,0.1986,0.1986

First-ever stroke

mortality[AgeGroups,Female]=0,0,0,0,0,0,0,0.12,0.12,0.14,0.11,0.18,0.14,0.16,0.17,0.18,0.2

First-ever stroke

mortality[AgeGroups,Male]=0,0,0,0,0,0,0,0.11,0.13,0.12,0.09,0.11,0.1,0.12,0.16,0.19,0.17

First-ever stroke onset rate for diabetic

population[AgeGroups,Female]=0,0,0,0,0.045,0.045,0.045,0.073,0.073,0.073,0.173,0.173,0.173,0.345,0.345,0.612,0.612

First-ever stroke onset rate for diabetic

population[AgeGroups,Male]=0,0,0,0,0.045,0.045,0.045,0.073,0.073,0.073,0.173,0.173,0.173,0.345,0.345,0.612,0.612

Fraction developing diabetes without diagnosis=0.1

Fraction of asymptomatic high risk screenings using OGTT=0.42

Fraction of diabetes detectable by FPGT=0.94

Fraction of diabetes detectable by OGTT=1

Fraction of early stage complication diabetes using OGTT=0.52

Fraction of normal weight infants[EthnicGroups,GenderGroups]=1

Fraction of obese infants[EthnicGroups,GenderGroups]=0

Fraction of overweight infants[EthnicGroups,GenderGroups]=0

Fraction of prediabetes detectable by FPGT=0.84

Fraction of prediabetes detectable by OGTT=1

Glucose screening of high risks baseline=0.89

Health access fraction baseline=0.85

Incidence of obesity base rate[AgeGroup0to4,EthnicGroups,GenderGroups]=0

Incidence of obesity base rate[AgeGroup10to14,EthnicGroups,GenderGroups]=0.1

Incidence of obesity base rate[AgeGroup15to19,EthnicGroups,GenderGroups]=0.1

Incidence of obesity base rate[AgeGroup20to24,EthnicGroups,GenderGroups]=0.1

Incidence of obesity base rate[AgeGroup25to29,EthnicGroups,GenderGroups]=0.1

Incidence of obesity base rate[AgeGroup30to34,EthnicGroups,GenderGroups]=0.05

Incidence of obesity base rate[AgeGroup35to39,EthnicGroups,GenderGroups]=0.05

Incidence of obesity base rate[AgeGroup40to44,EthnicGroups,GenderGroups]=0.005

Incidence of obesity base rate[AgeGroup45to49,EthnicGroups,GenderGroups]=0.05

Incidence of obesity base rate[AgeGroup50to54,EthnicGroups,GenderGroups]=0.05

Incidence of obesity base rate[AgeGroup55to59,EthnicGroups,GenderGroups]=0.05

Incidence of obesity base rate[AgeGroup5to9,EthnicGroups,GenderGroups]=0.05

Incidence of obesity base rate[AgeGroup60to64,EthnicGroups,GenderGroups]=0.01

Incidence of obesity base rate[AgeGroup65to69,EthnicGroups,GenderGroups]=0.01

Incidence of obesity base rate[AgeGroup70to74,EthnicGroups,GenderGroups]=0.01

Incidence of obesity base rate[AgeGroup75to79,EthnicGroups,GenderGroups]=0.01

Incidence of obesity base rate[AgeGroup80plus,EthnicGroups,GenderGroups]=0

Incidence of overweight base rate[AgeGroup0to4,EthnicGroups,GenderGroups]=0

Incidence of overweight base rate[AgeGroup10to14,EthnicGroups,GenderGroups]=0.1

Incidence of overweight base rate[AgeGroup15to19,EthnicGroups,GenderGroups]=0.1

Incidence of overweight base rate[AgeGroup20to24,EthnicGroups,GenderGroups]=0.1

Incidence of overweight base rate[AgeGroup25to29,EthnicGroups,GenderGroups]=0.1

Incidence of overweight base rate[AgeGroup30to34,EthnicGroups,GenderGroups]=0.05

Incidence of overweight base rate[AgeGroup35to39,EthnicGroups,GenderGroups]=0.05

Incidence of overweight base rate[AgeGroup40to44,EthnicGroups,GenderGroups]=0.05

Incidence of overweight base rate[AgeGroup45to49,EthnicGroups,GenderGroups]=0.05

Incidence of overweight base rate[AgeGroup50to54,EthnicGroups,GenderGroups]=0.05

Incidence of overweight base rate[AgeGroup55to59,EthnicGroups,GenderGroups]=0.05

Incidence of overweight base rate[AgeGroup5to9,EthnicGroups,GenderGroups]=0.05

Incidence of overweight base rate[AgeGroup60to64,EthnicGroups,GenderGroups]=0.01

Incidence of overweight base rate[AgeGroup65to69,EthnicGroups,GenderGroups]=0.01

Incidence of overweight base rate[AgeGroup70to74,EthnicGroups,GenderGroups]=0.01

Incidence of overweight base rate[AgeGroup75to79,EthnicGroups,GenderGroups]=0.01

Incidence of overweight base rate[AgeGroup80plus,EthnicGroups,GenderGroups]=0

Init diabetes to prediabetes coefficient[Female]=0.6

Init diabetes to prediabetes coefficient[Male]=1

Init dx diabetic with late stage complication

population[AgeGroups,Aboriginal,Female]=0,0,0,0,0,0,0,0,0,0,0,0,8,5,4,1,3

Init dx diabetic with late stage complication

population[AgeGroups,Aboriginal,Male]=0,0,0,0,0,0,0,0,0,4,2,14,3,4,2,2,1

Init dx diabetic with late stage complication

population[AgeGroups,Other,Female]=0,0,0,0,0,0,0,0,0,0,0,83,81,85,58,221

Init dx diabetic with late stage complication

population[AgeGroups,Other,Male]=0,0,0,0,0,0,0,0,28,21,155,57,115,110,142,142

Init dx diabetic without complication

population[AgeGroups,Aboriginal,Female]=0,1,1,5,8,15,24,32,39,43,41,33,19,13,9,4,3

Init dx diabetic without complication

population[AgeGroups,Aboriginal,Male]=0,2,1,4,4,9,18,20,26,28,26,24,13,8,4,2,1

Init dx diabetic without complication

population[AgeGroups,Other,Female]=2,6,11,20,40,51,72,97,137,168,198,188,192,193,198,186,285

Init dx diabetic without complication

population[AgeGroups,Other,Male]=2,10,16,26,37,44,58,96,135,202,251,258,235,241,221,166,183

Init normal weight

population[AgeGroups,Aboriginal,Female]=775,780,641,547,401,293,235,188,132,97,55,33,25,17,13,8,10

Init normal weight

population[AgeGroups,Aboriginal,Male]=842,806,707,562,373,274,212,177,110,71,39,26,20,14,9,6,4

Init normal weight

population[AgeGroups,Other,Female]=6078,6386,6637,6601,5944,4138,3532,5633,5674,4645,3267,2049,1714,1915,1618,1712,3487

Init normal weight

population[AgeGroups,Other,Male]=5870,6934,7039,6855,4895,3651,2940,3568,3147,3085,1976,1333,1431,1300,1308,1109,1631

Init obese

population[AgeGroups,Aboriginal,Female]=50,101,86,56,123,169,167,149,141,82,74,45,30,16,8,4,2

Init obese

population[AgeGroups,Aboriginal,Male]=87,88,98,78,115,158,150,140,118,60,52,36,25,13,6,3,1

Init obese

population[AgeGroups,Other,Female]=388,830,887,680,1088,1717,1844,2040,2270,2141,2358,1697,1458,1216,985,743,987

Init obese

population[AgeGroups,Other,Male]=608,753,979,945,1502,2105,2090,2824,3366,2600,2656,1824,1723,1233,823,546,404

Init overweight

population[AgeGroups,Aboriginal,Female]=139,171,184,176,306,300,311,238,201,146,107,70,30,25,18,11,10

Init overweight

population[AgeGroups,Aboriginal,Male]=142,165,199,196,284,280,281,224,169,106,75,56,25,21,12,8,4

Init overweight

population[AgeGroups,Other,Female]=1088,1405,1909,2127,2020,2027,2344,2439,2818,2649,2309,2070,1871,1639,2075,1647,2086

Init overweight

population[AgeGroups,Other,Male]=988,1416,1978,2386,3732,3737,3897,4509,4808,4627,3822,2876,1771,1972,1814,1496,1648

Init total diabetic with early stage complication

population[AgeGroups,Aboriginal,Female]=0,0,0,1,2,4,7,11,15,19,21,21,7,7,7,5,4

Init total diabetic with early stage complication

population[AgeGroups,Aboriginal,Male]=0,0,0,1,1,2,5,7,10,8,11,1,7,4,3,1,1

Init total diabetic with early stage complication

population[AgeGroups,Other,Female]=0,2,4,6,10,14,21,32,51,73,100,119,67,106,150,216,308

Init total diabetic with early stage complication

population[AgeGroups,Other,Male]=0,3,5,7,9,12,17,32,50,61,105,8,128,118,152,103,198

Init undx diabetic with early stage comp population elderly coefficient=0.1

Init undx diabetic with early stage comp population youth coefficient=0.5

Init undx diabetic with early stage complication population ethnic coefficient[EthnicGroups]=0.1

Init undx diabetic with early stage complication population gender

coefficient[GenderGroups]=0.1

Init undx diabetic without complication population elderly coefficient=0.5

Init undx diabetic without complication population ethnic coefficient[EthnicGroups]=1

Init undx diabetic without complication population gender coefficient[GenderGroups]=1

Init undx diabetic without complication population youth coefficient=0.8

Init undx prediabetic population elderly age coefficient=0.8

Init undx prediabetic population ethnic coefficient[EthnicGroups]=1

Init undx prediabetic population gender coefficient[GenderGroups]=1

Init undx prediabetic population youth age coefficient=1.5

Initial covered population by age ethnic gender

groups[AgeGroups,Aboriginal,Female]=963,1052,911,812,838,762,722,578,477,329,236,149,85,58,41,23,22

Initial covered population by age ethnic gender

groups[AgeGroups,Aboriginal,Male]=1071,1058,1004,835,779,712,650,544,400,240,165,119,70,47,27,16,9

Initial covered population by age ethnic gender

groups[AgeGroups,Other,Female]=5558,6202,6623,6782,7873,7293,6837,8129,8556,7547,6160,4286,3708,3435,3287,2970,4869

Initial covered population by age ethnic gender

groups[AgeGroups,Other,Male]=5841,6558,6983,6909,7595,7399,6989,8255,8435,7568,6041,4273,3344,3028,2555,2044,2346

Major macrovascular complication mortality switcher=1

Major macrovascular complication risk factor for RI=1

mortality coefficient dx diabetic with early stage comp=0.9

mortality coefficient dx diabetic with late stage comp=1.2

mortality coefficient dx diabetic without complication=0.9

mortality coefficient undx diabetic with early stage comp=1.2

mortality coefficient undx diabetic without complication=0.7

Mortality of dx prediabetic

population[AgeGroups,Aboriginal,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.232237,0.466201,1.27796,1.2801,1.97838,3.21877,6.39928,7.72477,12.9136,16.7054,31.3575,90.2742

Mortality of dx prediabetic

population[AgeGroups,Aboriginal,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,1.42541,2.14867,1.65607,1.99921,3.09877,5.65216,8.17938,13.8326,21.7865,32.4309,52.4955,125.264

Mortality of dx prediabetic

population[AgeGroups,Other,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.232237,0.466201,1.27796,1.2801,1.97838,3.21877,6.39928,7.72477,12.9136,16.7054,31.3575,90.2742

Mortality of dx prediabetic

population[AgeGroups,Other,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,1.42541,2.14867,1.65607,1.99921,3.09877,5.65216,8.17938,13.8326,21.7865,32.4309,52.4955,125.264

Mortality of normal weight

population[AgeGroups,Aboriginal,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.193531,0.388501,1.06497,1.06675,1.64865,2.68231,5.33273,6.83608,11.428,16.2189,30.4442,87.6448

Mortality of normal weight

population[AgeGroups,Aboriginal,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,1.18784,1.79056,1.38005,1.66601,2.58231,4.71013,6.81615,12.2412,19.2801,31.4863,50.9665,121.615

Mortality of normal weight

population[AgeGroups,Other,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.193531,0.388501,1.06497,1.06675,1.64865,2.68231,5.33273,6.83608,11.428,16.2189,30.4442,87.6448

Mortality of normal weight

population[AgeGroups,Other,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,1.18784,1.79056,1.38005,1.66601,2.58231,4.71013,6.81615,12.2412,19.2801,31.4863,50.9665,121.615

Mortality of obese

population[AgeGroups,Aboriginal,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0

.232237,0.466201,1.27796,1.2801,1.97838,3.21877,6.39928,7.72477,12.9136,16.7054,31.3575,90.2742

Mortality of obese

population[AgeGroups,Aboriginal,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,1.42541,2.14867,1.65607,1.99921,3.09877,5.65216,8.17938,13.8326,21.7865,32.4309,52.4955,125.264

Mortality of obese

population[AgeGroups,Other,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.232237,0.466201,1.27796,1.2801,1.97838,3.21877,6.39928,7.72477,12.9136,16.7054,31.3575,90.2742

Mortality of obese

population[AgeGroups,Other,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,1.42541,2.14867,1.65607,1.99921,3.09877,5.65216,8.17938,13.8326,21.7865,32.4309,52.4955,125.264

Mortality of overweight

population[AgeGroups,Aboriginal,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.160631,0.322456,0.883925,0.885404,1.36838,2.22632,4.42617,6.49427,10.8566,14.7592,27.7042,79.7568

Mortality of overweight

population[AgeGroups,Aboriginal,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,0.985908,1.48616,1.14545,1.38279,2.14332,3.90941,5.65741,11.6292,18.3161,28.6525,46.3795,110.67

Mortality of overweight

population[AgeGroups,Other,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.160631,0.322456,0.883925,0.885404,1.36838,2.22632,4.42617,6.49427,10.8566,14.7592,27.7042,79.7568

Mortality of overweight

population[AgeGroups,Other,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,0.985908,1.48616,1.14545,1.38279,2.14332,3.90941,5.65741,11.6292,18.3161,28.6525,46.3795,110.67

Mortality of undx prediabetic

population[AgeGroups,Aboriginal,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.232237,0.466201,1.27796,1.2801,1.97838,3.21877,6.39928,7.72477,12.9136,16.7054,31.3575,90.2742

Mortality of undx prediabetic

population[AgeGroups,Aboriginal,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,1.42541,2.14867,1.65607,1.99921,3.09877,5.65216,8.17938,13.8326,21.7865,32.4309,52.4955,125.264

Mortality of undx prediabetic

population[AgeGroups,Other,Female]=0.971777,0.0967517,0.193503,0.387007,0.290255,0.232237,0.466201,1.27796,1.2801,1.97838,3.21877,6.39928,7.72477,12.9136,16.7054,31.3575,90.2742

Mortality of undx prediabetic

population[AgeGroups,Other,Male]=1.56489,0.0967517,0.0967517,0.870765,1.25777,1.42541,2.14867,1.65607,1.99921,3.09877,5.65216,8.17938,13.8326,21.7865,32.4309,52.4955,125.264

Normal weight mortality switch=1

Obese mortality switch=1

Older age groups obesity

prevalence[WeightOldAgeGroups,Aboriginal,Female]=0.17,0.22,0.22,0.21,0.21,0.28,0.28,0.3,0.3,0.3,0.3,0.3

Older age groups obesity

prevalence[WeightOldAgeGroups,Aboriginal,Male]=0.15,0.21,0.21,0.27,0.27,0.27,0.27,0.28,0.28,0.28,0.28,0.28

Older age groups obesity

prevalence[WeightOldAgeGroups,Other,Female]=0.08,0.19,0.2,0.19,0.15,0.2,0.27,0.23,0.18,0.21,0.18,0.17,0.14

Older age groups obesity

prevalence[WeightOldAgeGroups,Other,Male]=0.11,0.24,0.26,0.22,0.31,0.21,0.25,0.28,0.35,0.24,0.19,0.15,0.09

Older age groups overweight

prevalence[WeightOldAgeGroups,Aboriginal,Female]=0.23,0.29,0.29,0.32,0.32,0.34,0.34,0.4,0.4,0.4,0.4,0.4,0.4

Older age groups overweight

prevalence[WeightOldAgeGroups,Aboriginal,Male]=0.36,0.5,0.5,0.48,0.48,0.51,0.51,0.44,0.44,0.44,0.44,0.44,0.44

Older age groups overweight

prevalence[WeightOldAgeGroups,Other,Female]=0.2,0.26,0.31,0.23,0.26,0.25,0.3,0.34,0.4,0.37,0.46,0.4,0.28

Older age groups overweight

prevalence[WeightOldAgeGroups,Other,Male]=0.36,0.4,0.47,0.41,0.42,0.52,0.53,0.48,0.35,0.47,0.44,0.49,0.41

Overweight mortality switch=1

Prediabetes incidence base rate normal

weight[AdultAgeGroups,EthnicGroups,GenderGroups]=0.01

Prediabetes incidence base rate normal

weight[AgeGroup10to14,EthnicGroups,GenderGroups]=0.01

Prediabetes incidence base rate normal

weight[AgeGroup15to19,EthnicGroups,GenderGroups]=0.01

Prediabetes incidence base rate normal

weight[ChildrenAgeGroups,EthnicGroups,GenderGroups]=0

Prediabetes onset age coefficient[AdultAgeGroups]=1

Prediabetes onset age coefficient[AgeGroup10to14]=0.1

Prediabetes onset age coefficient[AgeGroup15to19]=0.1

Prediabetes onset age coefficient[ChildrenAgeGroups]=0.1

Prediabetes onset obese multiplier=2.6

Prediabetes onset overweight multiplier=1.7

Prediabetes onset risk age multiplier[ElderlyAgeGroups]=1.15

Prediabetes onset risk age multiplier[YoungAgeGroups]=1

Prediabetes recovery rate[normalweight,AgeGroups,EthnicGroups,GenderGroups]=0

Prediabetes recovery rate[obese,AgeGroups,EthnicGroups,GenderGroups]=0

Prediabetes recovery rate[overweight,AgeGroups,EthnicGroups,GenderGroups]=0.03

Sensitivity coefficient for avg years develop early stage complication from undx diabetes=1

Sensitivity coefficient for avg years to develop diabetes from dx prediabetes=1

Sensitivity coefficient for Avg years to develop diabetes from undx prediabetes=1

Sensitivity coefficient for avg years to develop early stage complications from dx diabetes=1

Sensitivity coefficient for diabetes diagnosis=1

Sensitivity coefficient for diabetic with late stage complication mortality=1

Sensitivity coefficient for dx diabetic with early stage complication mortality=1

Sensitivity coefficient for dx diabetic without complication mortality=1

Sensitivity coefficient for dx prediabetic mortality=1

Sensitivity coefficient for incidence of obesity=1

Sensitivity coefficient for incidence of overweight=1

Sensitivity coefficient for prediabetes diagnosis=1

Sensitivity coefficient for prediabetes incidence rate obese=1

Sensitivity coefficient for prediabetes recovery rate=1

Sensitivity of FPGT screening for diabetes=0.65

Sensitivity of OGTT screening for diabetes=0.97

SHR birth rate[EthnicGroups,Female]=11.1/1000*0.49

SHR birth rate[EthnicGroups,Male]=11.1/1000*0.51

Tested fraction of early stage complication population due to symptoms=0.6

Time between screening coefficient for high risk asymptomatic elderly=1

Time between screening coefficient for high risk asymptomatic youth=2

Time between screenings coefficient for high risks asymptomatic ethnic groups[EthnicGroups]=1, 1

Time between screenings coefficient for high risks asymptomatic gender groups[GenderGroups]=1, 1

Time between screenings coefficient for undx early stage complication age groups[AgeGroups]=1

Time between screenings coefficient for undx early stage complication ethnic groups[EthnicGroups]=1, 1

Time between screenings coefficient for undx early stage complication gender groups[GenderGroups]=1, 1

Undx prediabetic mortality switch=1

Weight change age coefficient[AgeGroup0to4]=1

Weight change age coefficient[AgeGroup10to14]=0.1

Weight change age coefficient[AgeGroup15to19]=0.1

Weight change age coefficient[AgeGroup20to24]=0.1

Weight change age coefficient[AgeGroup25to29]=1

Weight change age coefficient[AgeGroup30to34]=1

Weight change age coefficient[AgeGroup35to39]=1

Weight change age coefficient[AgeGroup40to44]=1

Weight change age coefficient[AgeGroup45to49]=1

Weight change age coefficient[AgeGroup50to54]=1

Weight change age coefficient[AgeGroup55to59]=1

Weight change age coefficient[AgeGroup5to9]=1

Weight change age coefficient[AgeGroup60to64]=1

Weight change age coefficient[AgeGroup65to69]=1

Weight change age coefficient[AgeGroup70to74]=1

Weight change age coefficient[AgeGroup75to79]=1

Weight change age coefficient[AgeGroup80plus]=1

Weight change ethnic coefficient[Aboriginal]=1

Weight change ethnic coefficient[Other]=1

Weight change gender coefficient[Female]=1.1

Weight change gender coefficient[Male]=1

weight limit=0.01

Weighting switch=0

Years in each age group[AgeGroups]=5

Young age groups obesity

prevalence[WeightYoungAgeGroups,Aboriginal,Female]=0,0.2,0.23,0.23,0.08

Young age groups obesity

prevalence[WeightYoungAgeGroups,Aboriginal,Male]=0,0.2,0.26,0.35,0.09

Young age groups obesity

prevalence[WeightYoungAgeGroups,Other,Female]=0,0.08,0.09,0.09,0.05

Young age groups obesity

prevalence[WeightYoungAgeGroups,Other,Male]=0,0.08,0.11,0.14,0.05

Young age groups overweight

prevalence[WeightYoungAgeGroups,Aboriginal,Female]=0,0.21,0.23,0.23,0.24

Young age groups overweight

prevalence[WeightYoungAgeGroups,Aboriginal,Male]=0,0.16,0.21,0.26,0.29

Young age groups overweight

prevalence[WeightYoungAgeGroups,Other,Female]=0,0.17,0.19,0.18,0.23

Young age groups overweight

prevalence[WeightYoungAgeGroups,Other,Male]=0,0.13,0.17,0.21,0.29