ABSTRACT

Title of Dissertation: ENERGY DEMAND RESPONSES TO TEMPERATURE AND IMPLICATIONS OF CLIMATIC CHANGE

Anthony Dominic Amato, Doctor of Philosophy, 2004

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Climate is a major determinant of energy demand as well as the structure of the built environment. Climate change may alter energy demand and energy demand patterns. In this dissertation, I investigate the implications of climate change for energy demand by asking if energy demand sensitivities to temperature are place-specific, and if energy demand sensitivities to temperature reflect energy users' adaptations to prevailing climate? To answer these questions, energy demands for electricity, natural gas, and heating oil in seventeen states along the eastern seaboard of the United States are quantitatively analyzed. The states are on a north-south orientation to maximize inter-state climatic differences and presumably the degree of adaptation by energy users to climate.

Unique to this dissertation is the use of an impact-adaptation assessment framework to project energy demand responses to climate change scenarios. The net impacts on energy demand are related to both the system's sensitivity and adaptive capacity to changes in climate stimuli. In this study, a temporal analysis is developed and

used to quantify the historic sensitivities of energy demands to climatic variability while controlling for energy prices, daylight hours, and other socioeconomic factors. Based on the findings of the temporal analysis, the geographic analysis explores adaptation to current climate and provides for an estimate of the adaptive capacity of energy demand to climatic change. The final step of the assessment projects energy demand responses to climate change scenarios based on the temporal analysis findings as well as on a synthesis of the temporal and geographic analyses findings.

The principle findings of this dissertation are (1) that energy demand sensitivities to temperature vary by region, (2) that part of this variation is attributable to adaptations to regional climate conditions, and (3) that projections of energy demand responses to climate change should account for adaptations to changing climate characteristics.

In this dissertation, I develop methodological frameworks to assess the sensitivity and adaptive capacity of energy demand, present findings, discuss their implications, propose general recommendations for improving the practice of modeling climate change impacts on energy demand, and offer suggestions for future research.

ENERGY DEMAND RESPONSES TO TEMPERATURE AND IMPLICATIONS OF CLIMATIC CHANGE

by

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LIST OF ABBREVIATIONS

ASHRAE	American Society of Heating, Refrigerating and Air-conditioning Engineers
BAU	Business-as-usual
BPT	Balance Point Temperature
BTU	British Thermal Unit
CBECS	Commercial Building Energy Consumption Survey
CDD	Cooling Degree-days
CO_2	Carbon Dioxide
DOE	Department of Energy
EIA	Energy Information Administration
GHG	Greenhouse Gases
HDD	Heating Degree-days
IPCC	Intergovernmental Panel on Climate Change
kWh	Kilowatt hours
MMcf	Million metric cubic feet
NCDC	National Climatic Data Center
NOAA	National Oceanic and Atmospheric Administration
PPMV	Parts per Million by Volume
RECS	Residential Energy Consumption Survey
UNCED	United Nations Conference on Environment and Development
UNEP	United Nations Environmental Program
UNFCCC	United Nations Framework Convention on Climate Change

1. Introduction

1.1 Statement of the Problem

Changes in global climate are occurring at rates exceeding those attributable to natural variability because of increases in atmospheric concentrations of heat-trapping gases (Karl and Trenberth, 2003). Human-related activities, namely the combustion of fossil fuels and land-use changes, are the principal factors modifying atmospheric composition. Such atmospheric changes will continue to alter temperature, precipitation, humidity, wind, sea level, and 'extreme events', all of which impact natural and human systems.

Many members of the international community have expressed concern regarding the rate and consequences of climate change. In 1992, at the United Nations Conference on Environment and Development (UNCED), over 160 nations ratified the United Nations Framework Convention on Climate Change (UNFCCC). The ultimate objective of the UNFCCC, as expressed in Article 2, is "to achieve…stabilization of greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic interference with the climate system". The determination of what might be regarded as *dangerous* is directly related to the extent to which climate change will affect natural and human systems. To decipher the consequences of these affects, numerous impact assessments have been conducted in an attempt to better understand climate change impacts and to develop appropriate responses. Consequently, the science of impact assessment has been continually refined through the development of more realistic assumptions and improved modeling techniques. Two key features increasingly emphasized in the impact literature, which are also relevant to this dissertation, are the importance of scale and the integration of adaptation.

The choice of scale should be related to the focus of the assessment, or what is being asked, as climate change impacts on natural and human systems vary in different locations and are therefore scale-dependent. As the IPCC advises, assessments must place greater emphasis upon utilizing scales where "the impacts of climate change are felt and responses are implemented" because knowledge of place-specific sensitivities to climate change and response capabilities is an essential ingredient to modeling impacts (IPCC, 2001a, p.25). Increasingly researchers have recognized the value of producing higher spatial resolution analyses to accurately portray what will occur on the ground as opposed to lower resolution models that only offer generic responses (Wilbanks and Kates, 1999). Moreover, for impact assessments to be relevant to decision-makers they must provide information on scales that concern them (Easterling, 1997).

The integration of adaptation is also essential to impact assessment because the extent to which a system will be affected depends on the system's sensitivity to changes in climate stimuli *and* the system's ability to adapt to those changes to moderate potential damages or take advantage of opportunities associated with changes in climate stimuli. Consequently, estimates of future adaptations are a necessary element of accurate analyses of climate change impacts (IPCC, 2001a).

Although significant progress has been achieved in modeling and assessing climate change impacts on human systems, past assessments on energy demand have typically been performed at large geographic scales and have failed to adequately account for adaptation to climate change. This project addresses those modeling gaps using the impact-adaptation assessment framework along with a host of other innovative methodologies.

1.2 Purpose of the Dissertation

The purpose of this dissertation is to explore potential impacts of climate change on energy demand. To achieve this goal, this dissertation uses the impact-adaptation assessment framework. According to the impact-adaptation assessment framework the *net impact* of climate change on a system is a function of (1) the *sensitivity* of the system to changes in climate stimuli and (2) the *adaptive capacity* of the system to moderate potential damages or to take advantage of opportunities associated with changes in climate. These factors – sensitivity and adaptive capacity – are independently examined for energy demand through two distinct analytical methodologies that are developed and applied in this dissertation.

In assessing the *sensitivity* of energy demand, I have developed a temporal analysis methodology, which quantifies historic energy demand sensitivities to climate variability while controlling for such factors as energy prices and daylight hours. For this research, climate variability and change is simulated with monthly temperature variables. The methodology specifically accounts for place-specific characteristics of energy demand, many of which are indicative of adaptations by energy users to current climate. Seventeen states as well as their three overarching census divisions are analyzed. Together the analyzed states represent 32% of the total energy used in the United States. In developing the energy demand models, state and census divisional population-weighted temperatures are formulated and subsequently converted to degree-day variables. Heating and cooling degree-days, which are indices of coldness and hotness respectively, are derived using an iterative procedure to enable optimal specification that reflects local perceptions of ‘cold’ and ‘hot’. In addition to quantifying place-specific energy demand sensitivities, the temporal analysis also explores the scalar dynamics of energy demand sensitivities using multi-level analysis, which compares the state-level and census divisional-level findings.

The *adaptive capacity* of energy demand to climate is explored in this dissertation through a geographic analysis methodology. The geographic analysis compares variation in states’ energy demand sensitivity functions developed in the temporal analysis because, as is a thesis of this dissertation, built into energy demand sensitivities to temperature variability are energy users’ adaptations to prevailing climatic conditions. In examining this thesis, the states are on a north-south orientation – spanning from Maine to Florida – to maximize differences in climate and presumably the level of adaptation to climate. If patterns emerge between current climate conditions and energy demand sensitivity functions, then changes in climate may induce new adaptations to the new climate characteristics. Based on the observed correlation between current adaptation levels and current climate, adaptation to climate change scenarios can then be endogenously specified in projections of energy demand responses to climate change.

1.3 Research Questions

The objective of this dissertation is to provide a better understanding of potential energy demand responses to climate change. A fundamental premise of this dissertation is that to accurately assess future energy demand responses to climate change both energy demand's sensitivity to temporal variations in temperature *and* adaptations to spatial variations in climate need to be understood. To this end the dissertation asks:

- *Are energy demand sensitivities to temperature place-specific? If so, in what ways?*
- *Are adaptations by energy users to prevailing climate reflected in energy demand sensitivities to temperature? If so, in what ways?*

1.4 Significance of the Dissertation

This study differs from earlier efforts because it utilizes the impact-adaptation assessment framework to analyze the potential impacts of climate change on energy demand. Rather than assessing impacts based exclusively on the historic sensitivity of energy demand to climate variability, this analysis utilizes a more complete framework that examines energy demand responses to climate change. Consequently, this dissertation makes useful and necessary contributions to the impact-adaptation literature and to the policy debate on energy implications of climate change. Such contributions are needed because, at present, generalizations concerning likely impacts on energy demand range from "perceptible but modest" (IPCC 1996, p.376) to "profound" (UNEP 1998, p.11-1).

First, this dissertation contributes to the impact-adaptation literature by integrating key features required for impact assessment, namely scale and adaptation, into energy demand models and thus allows for a more complete framework to examine energy demand responses to climate change than past assessments.

Scale was considered during the initial phases of the assessment and subsequently a number of innovative methodologies were developed that better characterize place-specific energy demand sensitivities to temperature. These innovations consist of place-specific definitions of 'hot' and 'cold', accounting for the temporal dynamics of energy demand sensitivity to 'hot' and 'cold', and controlling for hours of daylight in each month because they are correlated with monthly temperature.

This dissertation also makes significant contributions to the impact-adaptation literature, because it is the first project to examine adaptation of energy demand to prevailing climate and likewise the first to model the adaptive capacity of the energy demand to climate change scenarios. Adaptation to climate change is modeled as an endogenous process based on current adaptations to prevailing climates. The assessment framework developed in this dissertation also provides an applicable structure for assessments at different geographic locals.

Second, this dissertation adds to and expands upon the policy debate on the energy implications of climate change. In particular, my study provides decision-makers with scenarios of future energy demand under a business-as-usual case and under a case with adaptation. By projecting impacts of climate change with and without adaptation the findings provide a basis for discussing the need for adaptation measures, the pros and cons of potential response strategies, and assists in identifying where additional research may have the highest payoff from an adaptation policy perspective. Moreover, because adaptation measures will need to be tailored to local conditions and decision-making processes the analysis presents useful information that is at scales relevant to decision makers.

1.5 Organization of the Dissertation

The organization of this dissertation is as follows. After this introduction, chapter 2 summarizes the science of climate change and reviews potential human responses to those changes. To provide a theoretical foundation for this study, special attention is paid to the adaptation response and assessment framework, including recent emphasis in the literature on the importance of spatial scale.

Chapter 3 examines the impacts of climate and climate change which specifically relate to the energy sector as well as recent assessments of these impacts. Section 3.1 details the existing literature on energy supply infrastructure vulnerability to climate and climate change. Section 3.2 reviews and critiques research into the effects of climate on energy demand along with research addressing the potential impacts of climatic change on energy demand. Moreover, this section argues that assessments of energy demand should be at the regional level and that the temporal dynamics of energy demand should be considered in projections of future energy demand.

Chapter 4 presents the research methods utilized in this dissertation. The chapter begins with an introductory section, which places energy demand impacts in the context of the impact-adaptation assessment framework. Section 4.2 then moves on to discuss and develop the methodological frameworks, which include a temporal analysis and a geographic analysis. The frameworks, respectively, estimate place-specific energy demand *sensitivities* to temperature and energy demand *adaptations* to prevailing climate. Section 4.3 outlines how the climate change scenarios are developed and applied to the energy demand response functions to project future energy demand under climate scenarios.

Chapter 5 examines the data, relevant background factors, and historic energy demand sensitivities to temperature. Section 5.1 details the data used in quantifying energy demand sensitivities and adaptations to climate. In particular, the section discusses the data sources, collection methods, and manipulation techniques. Section 5.2 details background factors, many of which represent adaptations to climate, that are relevant in explaining quantitative findings, but which are not available in sufficient spatial or temporal resolution to be included in the energy demand statistical models. The section provides a snapshot of regional characteristics of residential dwellings and commercial buildings that are pertinent to understanding the energy demand-temperature relation. Section 5.3 discusses and graphically presents the historic energy demand-temperature relations using scatter plots of energy demand and population-weighted temperature. The section is offered as a verification benchmark for the statistical findings put forth in the next chapter.

Chapter 6 details and discusses the statistical findings of the temporal and geographic analyses. In chapter 7, projections of energy demand response with and without adaptation to climate change scenarios are presented. Chapter 8 closes with a concluding chapter, which consists of a summary of the dissertation, a discussion of methodological lessons for future impact assessments of energy demand, and recommendations for future research.

2. Climate Change and Societal Response Options

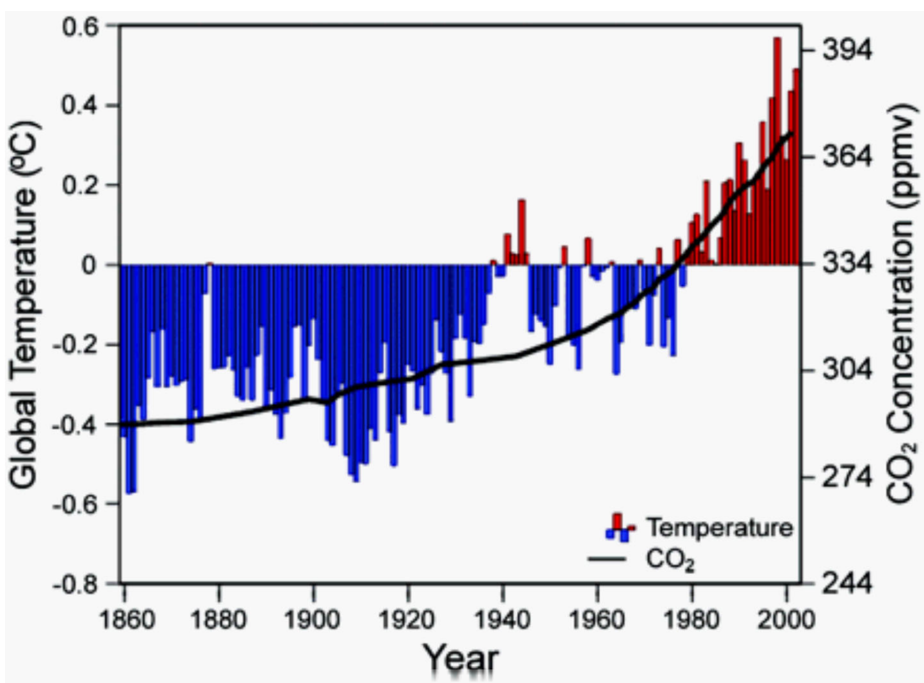
2.1 Science of Climate Change

Earth is inhabitable because of its distance from the sun and because it possesses a number of atmospheric gases which have the ability to absorb and reradiate terrestrial infrared radiation. Collectively these gases are commonly referred to as 'greenhouse gases' (GHG) because, analogous to the glass of a greenhouse, they allow solar radiation in while trapping much of the heat inside. Without the greenhouse effect of these atmospheric gases the Earth's temperature would be 0°F (-18°C); with it, the Earth's average surface temperature is about 57°F (14°C) (Schneider, 1997). The most important greenhouse gases in the Earth's atmosphere include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), water vapor (H_2O), ozone (O_3), and the chlorofluorocarbons (CFCs including CFC-12 (CCl_2F_2) and (CFC-11 (CCl_3F)).

Human-related activities are causing the climate to change at rates exceeding those attributable to natural variability (Karl and Trenberth, 2003). The dominant mechanism by which humans alter global climate is by interference with natural flows of energy via changes in atmospheric composition. The changes in atmospheric composition result from anthropogenic emissions of greenhouse gases. Moreover, because atmospheric concentration is a product of accumulated emissions of greenhouse gases with long atmospheric lifetime – ranging from decades to centuries – anthropogenic global warming is a phenomenon that is occurring and will continue to occur over the next several decades, even with drastic cuts in emissions.

The primary, human-controlled greenhouse gas that is enhancing the heat-trapping ability of the atmosphere is CO_2, largely from the combustion of fossil fuels for societal energy use. Atmospheric CO_2 concentration has risen 31% since pre-industrial times, from 280 parts per million by volume (ppmv) to more than 370 ppmv today (see Figure 1). Concurrent with, and attributable to, the increase in CO_2 concentration is the increase in global average surface temperature. The scientific consensus is that globally averaged surface air temperature will warm between 1.4 to 5.8°C by 2100 relative to 1990 and globally averaged sea level will rise 0.09 to 0.88 meters by 2100 (IPCC, 2001b).

Figure 1. Global Temperature and Atmospheric CO_2 Concentrations (Source: Karl and Trenberth, 2003)



While there is a broad consensus in the scientific community that climatic change is real there remains considerable uncertainty into exactly how climate will change, how long it will last, and the magnitude of the resulting effects (National Research Council, 2001). One such uncertainty, for example, is if accompanying changes in climatic averages will be changes in climate variability, which would in turn lead to possible changes in the frequency and intensity of 'extreme' weather events. Extreme weather events are perhaps an even larger concern from a societal perspective than changes in climatic averages (Changnon, 2000; Katz, 1992). Changes in climate, whether averages or extremes, are anticipated to have serious repercussions for socio-economic (IPCC, 2001a) and biological systems (IPCC, 2002a).

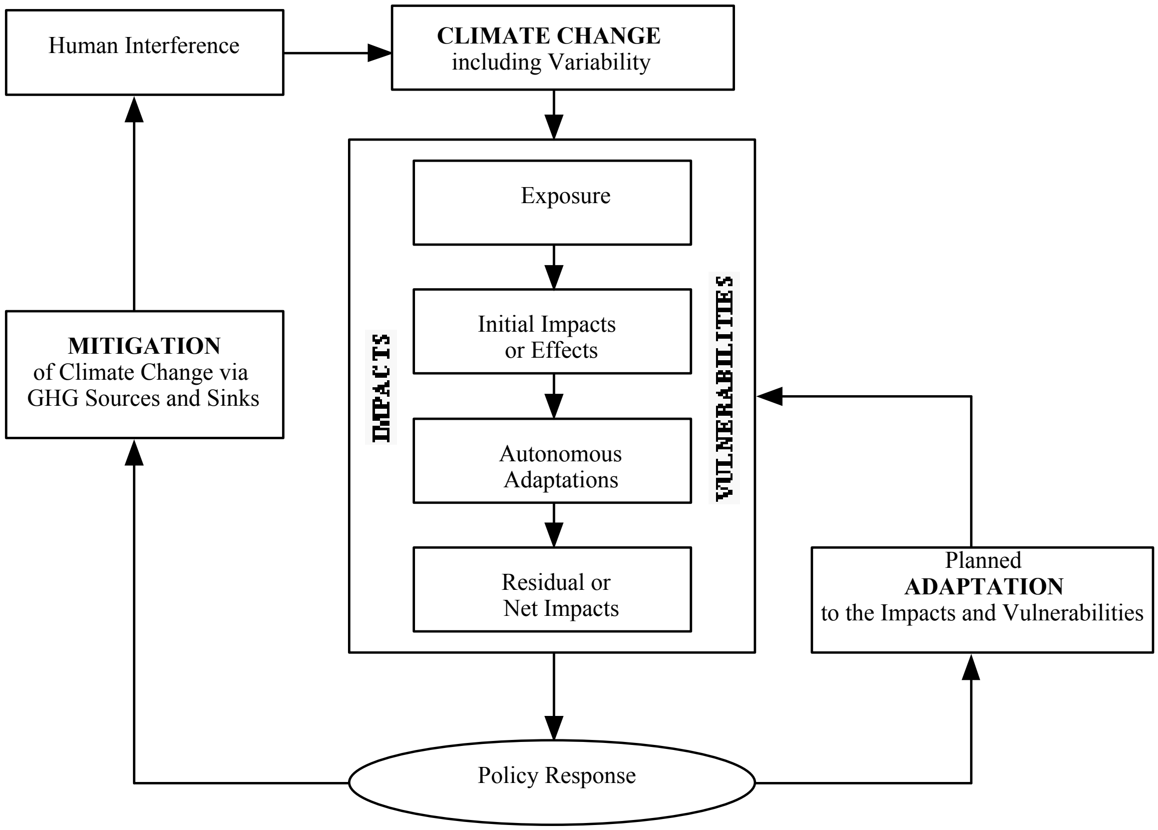
2.2 Societal Response Options to Climate Change

Growing scientific certainty and societal awareness of climate change and its related impacts have led to a deepening resolve among some to address the issue. Global concerns over climatic change are reflected in the 1992 United Nations Framework Convention on Climate Change (UNFCCC), whose stated objective is the stabilization of GHG concentrations in the atmosphere at levels that would prevent dangerous anthropogenic interference with the climate system. Since then all major industrialized countries except the United States, the Russian Federation, and Australia have ratified the Kyoto Protocol, a binding agreement whereby industrialized countries commit themselves to reducing their overall emissions of six greenhouse gases by 5% below 1990 levels over the period between 2008 and 2012, with specific targets varying from country to country. Without ratification by either the United States or the Russian Federation the Kyoto Protocol will not enter into force.

While international efforts to secure national collaboration in forging climate change protection measures have fallen short, there are some positive developments at the sub-national level. In countries around the globe – including those that have not ratified the Kyoto Protocol – are significant grassroots efforts to adopt policies to reduce greenhouse gas emissions or prepare for the impacts of climate change. Universities, firms, municipalities, and states are undertaking a wide range of climate change emission reduction policies and protection measures (Rabe, 2002; Watson, 2003). Collectively, these policies and measures represent a surprisingly vibrant bottom-up approach to addressing global climate change, even while the theory of 'free-riding' would predict that local decision makers should find it difficult to reduce their emissions for the benefit of the global climate (Kousky and Schneider, 2003).

The response alternatives to climate change available to society are *mitigation* and *adaptation* (see Figure 2). Mitigation responses limit human interference with the climate system either by reducing or counter-balancing anthropogenic greenhouse forcing. Adaptation responses modify the impacts or vulnerability of systems to climatic change and its effects. The next sections more fully detail the mitigation and adaptation responses to climate change and the current state of research understanding into each.

Figure 2. Societal Response Options to Climate Change. (*reproduced from:* Smit, 1999)



2.2.1 Mitigation Response

The mitigation response to climate change is actually a collection of three strategies: (1) GHG emission limitation, (2) carbon removal and storage, and (3) geoengineering (IPCC, 2001c; Nakicenovic, 1993). Each of these mitigation strategies attempt to limit human interference with the climate system either by reducing or counter-balancing anthropogenic greenhouse forcing. The options for GHG limitation strategies include increasing efficiency of energy generation, distribution and end-use technologies, shifting to less carbon-intensive or non-carbon technologies, and improved energy management. GHG limitation assessments typically evaluate different global greenhouse gas emission pathways to various concentration stabilization levels, often calculating the societal costs using top-down economic models (Wigley, 1996; Hoffert, 1998). Since the climate change debate has, to date, overwhelmingly focused on the limitation response alternative (Pielke, 2000), such as the Kyoto Protocol, an array of concepts (i.e. decarbonization) and tools (i.e. GHG emission calculators and databases) have been developed.

The second mitigation option, carbon removal and storage, involves the use of forests, agricultural lands, and other natural systems to biologically mitigate the accumulation of GHG in the atmosphere. Biological mitigation is possible via three strategies: (1) conservation of existing carbon pools, (2) sequestration by increasing the size of carbon pools, and (3) substitution of fossil fuels and energy intensive construction products by sustainably-produced biological products (IPCC, 2001c).

Geoengineering, the third mitigation option available to society, is the "deliberate manipulation of the planetary environment" (Keith, 2000, p.246). For example, deploying giant reflectors in orbit to scatter sunlight away from earth and thereby reduce solar input. While the precise distinction between geoengineering and other mitigation strategies remains 'fuzzy', Keith argues that the difference between geoengineering and mitigation is when a technology acts by counterbalancing an anthropogenic forcing rather than reducing it (Keith, 2000). The geoengineering strategy has to date generally been ignored by the policy community as a viable response alternative. This is largely due to the unknown consequences of deliberately manipulating the earth system to counteract anthropocentric climate change (Schneider, 2001).

Through effective mitigation - whether it is limitation, carbon storage and management, or geoengineering - the rate and extent of climatic change could be limited.

The alleviation of climate change impacts via the mitigation response would result in global benefits and, hence, the response strategy is a public good because it is non-rival and non-excludable (Kane, 2000).

2.2.2 Adaptation Response

The other response alternative to climate change available to society is *adaptation*, which refers to "changes in processes, practices, or structures to moderate or offset potential damages or to take advantage of opportunities associated with changes in climate" (IPCC, 2001a). Adaptation is a critical component in understanding the impacts of climatic change on a system or sector because the impacts are a function of the sensitivity of a system or sector to changes in climate and its ability to adapt to new climatic conditions. The net impact of a change in a climatic stimuli on a biological or socioeconomic system can be expressed by the following relationship:

$$\text{Net Impact} = f\,(\text{exposure, sensitivity, adaptive capacity})$$

In the net impact function, *exposure* is the condition of a system to being subject to climatic stimuli. *Sensitivity* is the degree to which a system is affected, either adversely or beneficially, by climatic stimuli. *Adaptive capacity* is the potential for adaptation to climatic stimuli, that maintains, preserves or enhances the viability of the system. Adaptations are responses that alter the exposure and/or sensitivity of the system to the climatic stimuli to decrease detrimental impacts on the system.

Adaptations can be in the form of *reactive* adaptations and *anticipatory* adaptations (see Figure 3) (IPCC, 2001a). Reactive adaptations are adaptations by agents within a system that occur as a purely natural or spontaneous response to stimuli after the fact. In unmanaged ecosystems, for example, responses to climate stimuli are always reactive because there are no forward-looking planners. Anticipatory adaptations, on the other hand, involve the conscious undertaking of actions in the expectation of climatic change. With regards to an energy user, a reactive adaptation to increased mean summer temperature would be using air conditioning more frequently or intensely. An anticipatory adaptation, on the other hand, might entail planting shade trees to reduce solar input into the building envelope and thereby reduce energy consumption and expenditure.

Figure 3. Classifications of Adaptations to Climate Change, (source Klein, 1999).

		Anticipatory	**Reactive**
Natural Systems			* Changes in length of growing season; * Changes in ecosystem composition; * Wetland migration.
Human Systems	**Private**	* Purchase of insurance; * Construction of house on stilts; * Redesign of oil rigs.	* Changes in farm practices; * Changes in insurance premiums; * Purchase of air-conditioning.
	Public	* Early warning systems; * New building codes; * Incentives for relocation.	* Compensatory payments, subsidies; * Enforcement of building codes; * Beach nourishment.

Adaptations are also classified in the literature by who or what does the adapting. In human systems, adaptation is commonly divided into adaptations by private agents and adaptations by public agents. The climate change literature generally focuses on anticipatory adaptation by private or public agents.

In human systems, the potential for adaptation is to a large part determined by social, economic, technological, and institutional factors (Kelly, 2000; Adger, 1999; Handmer, 1999; Yohe, 2000). Accordingly, research indicates that less developed countries are more vulnerable to climate change and that sustainable development is a robust adaptation strategy (Beg et al., 2002). Enhancement of adaptive capacity represents a practical means of reducing vulnerability to climate change.

The adaptation response represents a form of 'self-insurance' against the realization of climate change impacts (Kane, 2000). Therefore, as opposed to the mitigation response alternative, which is a public good, the adaptation response benefits only those doing the adapting.

Estimates of climatic impacts are significantly influenced by assumptions about the level and types of adaptation of the sector or system under study. Early models of climate change impacts assumed no adaptation. Most notably, agriculture models calculated potential changes in crop yields under various climate change scenarios assuming farmers neglected changing conditions and continued to grow crops, even if the crops are ill-suited for new climatic conditions. Subsequently, impact models assuming no adaptation are commonly referred to as modeling on the "dumb farmer" assumption. The "dumb farmer" assumption is a metaphor for any agent or system that is assumed not to anticipate or respond to changing climate conditions. These first climate impact models were followed by overly optimistic models that assumed perfect adaptation to changing climatic conditions, and were thus cited as "clairvoyant farmer" models. Adaptation to climate and potential adaptations to climate change likely will fall somewhere in between the two cases. Optimal adaptations to climate change are, however, unlikely because of institutional and technological inertia as well as because of the noise of inherent natural climate variability that masks slowly changing climate trends (Schneider et al., 2000)

Two distinct types of adaptation analyses are common in the literature (see Table 1) (Smit et al, 1999; Burton et al., 2002). The first type of adaptation analysis is part of impact assessment where the main emphasis is on understanding what adaptations are likely and under what circumstances they are likely to occur. These are positive analyses that address Article 2 of the UNFCCC. The second type of adaptation analysis is part of policy evaluation and the emphasis is on the design, effectiveness, and prioritization of specific adaptation measures and policies. These analyses are normative in nature and address Article 4 of the UNFCCC. The present study is of the first type of adaptation analysis, an impact assessment of climate change on energy demand.

Table 1. Places for Adaptation Analyses in IPCC, (Smit et al., 1999).

	Adaptation as part of IMPACT ASSESSMENT	Adaptation as part of POLICY EVALUATION
Analytic Function	Positive	Normative
Purpose	Predict, Estimate Likelihood	Evaluate, Prescribe
Central Question	What Adaptations are Likely?	What Adaptations are Recommended?
UNFCCC Article	Art. 2 are the impacts likely to be dangerous for ecosystems, food production and sustainable economic development?	Art. 4 which measures should be formulated and implemented to facilitate adequate adaptation?

2.2.2.1 Reasons for Recent Focus on Adaptation

The dynamics of the climate system and long-lived nature of greenhouse gases indicate that even with aggressive mitigation policies climate is likely to change. Therefore, effectively addressing climate change is increasingly recognized by policy-makers to involve a combination of mitigation *and* adaptation (Pielke, 1998; Pielke et al., 2000; Burton, 2002). The appropriate societal balance between mitigation and adaptation depends on the costs and benefits associated with each strategy. However, as the IPCC notes "little attention has been paid to any possible tradeoff between both types of options" (IPCC, 1996a, p.250). The lack of attention to the tradeoffs is a result of the fact that few assessments examine the adaptation process and its associated costs (Fankhauser et al., 1999). Moreover, as Smithers and Smit argue, while "adaptation is frequently referred to in scholarly work and policy discussions related to climate, there is no common understanding of what is meant by the term, let alone how the prospects for adaptation might best be analysed" (Smithers and Smit, 1997, p.130). As a consequence, little is known of the "how, when, why, and under what conditions adaptations actually occur in economic and social systems" (Smithers and Smit 1997, p.129).

The climate change and impact assessment research literatures provide a number of reasons why adaptation as compared to mitigation has received so little attention by policy-makers and impact assessment modelers. The first reason is that although the processes underlying both the cause and consequences of climate change occur at the local level, the issue itself was originally cast as a global problem (Wilbanks and Kates, 1999). Defining climate change as a global-scale problem has enticed assessments and policy responses to find solutions at the same scale (Cebon, 2000; Pielke, 1998). Not surprisingly the majority of climate change assessments have concentrated on mitigation options since they can be formulated at international fora and implemented at a coarse geographic resolution. In contrast, assessments of adaptation strategies are contingent upon the place-specific characteristics of the system that must adapt (Easterling, 1997).

A second reason policymakers have concentrated on mitigation is that a policy focus on adaptation gives the perception of sounding "soft" on mitigation (Burton, 1994). As climate change is regarded by the international community as a serious problem warranting serious attention, nations want to be perceived as proactively seeking solutions.

A third reason is that adaptation involves a certain degree of "fatalism" and as a "passive acceptance" that humans are causing climate change, humans are unable to stop the climate from changing and, hence, society must rely on a technological fix to avoid negative repercussions (Burton, 1994). As Nordhaus observes, "mitigate we might; adapt we must" (Nordhaus, 1994, p.189).

A fourth reason is that climate models are not spatially-detailed enough to give precise predictions of regional climate change (Giorgi, 2000), which in turn make it difficult to assess the impacts or the effectiveness and costs of adaptation strategies. To illustrate, about two-thirds of the integrated assessment models of climate change have geographic-specificity of either the entire globe or whole continents (Wilbanks and Kates, 1999). Therefore, adaptation studies are forced to rely on a scenario-based or "if-then" approach to assess plausible outcomes to possible climate scenarios.

2.2.2.2 Issues of Scale in Adaptation Assessments

Accompanying the recent emphasis in the climate change research literature on adaptation assessments are calls by decision-makers for these assessments to be performed at finer spatial scales where, as the IPCC observes, “the impacts of climate change are felt and responses are implemented” (IPCC, 2001a, p.25). To date, as Wilbanks and Kates note, “what is striking about impact assessment is its generic quality and lack of place-specific content, when ‘average impacts’ over large areas have limited value for discussions of place-oriented response” (Wilbanks and Kates, 1999, p.615). The importance of place-specific characteristics in determining the sensitivity and adaptive capacity of a system or sector to climatic change induced stimuli requires spatial representation at a finer resolution than current assessments employ (Easterling, 1997). Recent quantitative studies validate this conclusion. For example, a country-level analysis by Mendelsohn et al. finds highly country-specific sectoral market impacts of climate change leading the authors to conclude that detailed spatial representation has policy relevance for impact assessment models (Mendelsohn et al., 2000).

The realization that the “challenge is not to establish the preeminence of any particular scale, but rather to match scales of explanation, processes, and patterns in a realistic and effective way” (Clark, 1985, p.21) has induced global change researchers to increasingly address the multi-scale nature of global environmental problems (Cash and Moser, 2000). In fact, the IPCC’s Fourth Assessment Report (FAR), which is due for completion in 2007, has already indicated that greater emphasis will be given to assessing regional impacts of climatic change (IPCC, 2002b).

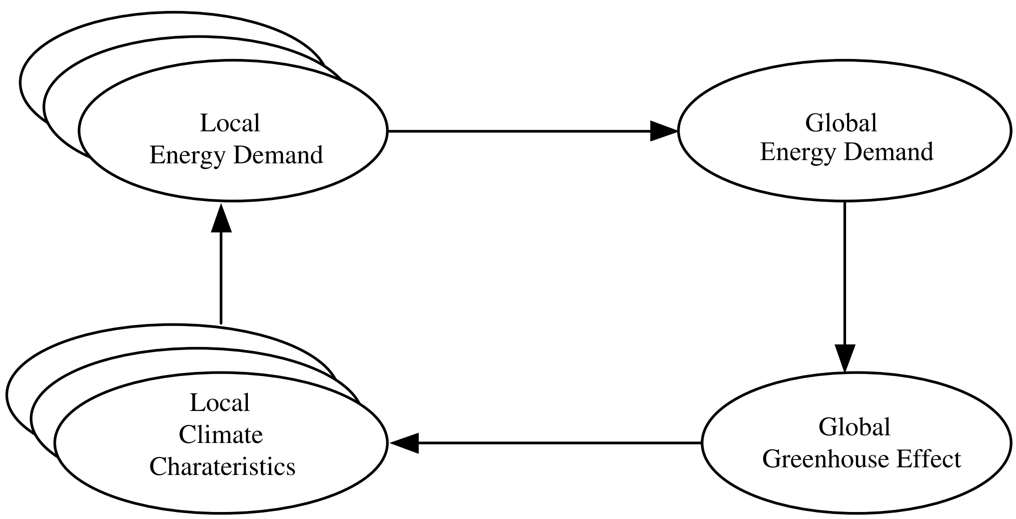
Cash attributes the recent downscaling of "global" change assessments to the regional and local levels to be a result of two drivers (Cash, 2000). The first driver, which is a supply-side push, is the recognition by the scientific community that a grasp of fine-scale structures is critical to understanding the larger system in which they are embedded. The second driver, a demand-side pull, is that decision-makers at the sub-national and local levels are demanding information about global environmental problems at scales compatible with their policy influence. Higher resolution impact assessments or "distributed assessments" are more aligned with the policy-levers available to decision-makers at the local, regional or sub-national level (Cash, 2000). Additionally, the findings of assessments conducted at the local or regional level provide for greater stakeholder responsiveness and mobilization because the impacts are viewed as occurring 'on the ground' (Shachley and Deanwood, 2002).

In summary, climate change researchers are increasingly producing adaptation assessments to compliment the current fleet of mitigation analyses and to assess the tradeoffs and complimentarities between mitigation and adaptation alternatives. Furthermore, adaptation assessments are being conducted at finer spatial scales because (1) they offer a more realistic representation of a system or sector's response to climate stimuli due to the place-specific characteristics of the system or sector, and (2) decision-makers at the national, sub-national, and local levels require information at scales compatible with their policy leverage.

3. Climatic Impacts on Energy Supply and Demand

The interactions between climate and energy systems are complex and occur at varying spatial and temporal scales (see Figure 4) (Bach et al. 1980; Jager, 1983). *Localized* emissions from the combustion of fossil fuels produce *short-lived*, *local* air pollution as well as the accrual and diffusion of *long-lived*, heat-trapping gases in the *global* atmosphere. The increasing atmospheric concentration of heat-trapping gases warms the surface of the Earth causing non-uniform changes in *local* climates (IPCC, 2001b).

Figure 4. Interactions between Climate and Energy Systems.



Anthropogenic energy use is affecting climate and, at the same time, local climatic conditions are directly and indirectly impacting energy systems (Warren, 1981; Sailor, 1997). Directly, energy supply infrastructure – such as power plants, pipelines, and transmission towers and distribution lines – are impacted by climate conditions such as temperature, humidity, precipitation, snow, and wind. Indirectly, climatic conditions are a major determinant of energy demand, largely due to requirements for indoor space-conditioning services (i.e. heating and cooling).

The majority of climate change research assessments examine how anthropogenic actions impact the climate system and what measures can mitigate these impacts. To date, mitigation assessments have prevalently focused on the energy sector, as it is the major culprit behind human-induced global climate change (Hoffert, 1998; Grubb, 2001; Wigley, 1996; Nakicenovic, 1993).

In contrast, impact-adaptation assessments routinely concentrate on non-energy sectors that are anticipated to be particularly sensitive to climate change such as agriculture (Smit and Skinner, 2002; Alexandrov, 2000), urban infrastructure (Schreider and Smith, 2000), water supply (de Loe, 2001; Vorosmarty 2000), and tourism (Breiling and Charamza, 1999; EDF, 1997). Little research addresses the impacts of climatic change on the energy sector (UNEP, 1998). The limited research is surprising given (1) that energy demand is inherently climate-sensitive and (2) that energy infrastructure is generally long-lived and therefore will likely experience climatic changes.

The following sections review the literature on the impacts of climate and climate change on the energy sector. Impacts on both the supply and demand-sides are discussed.

3.1 Energy Supply Infrastructure Vulnerability to Climate and Climate Change

Energy supply infrastructure is particularly sensitive to climate, climate extremes, and climate change (UNEP, 1998). Increasing temperatures, changes in wind and precipitation patterns and intensities, changes in the frequency of extreme events, variations in humidity and cloudiness could all affect the energy supply infrastructure. With the nation's energy system underpinning other infrastructure systems such as water, telecommunications, financial markets and transportation the reliability of the energy system is increasingly recognized as an urgent concern (Peerenboom et al., 2002). Currently, the annual cost of electric power disruptions to the US economy is estimated to be $29 billion due to lost productivity (Hoffman, 1996). Because the energy supply infrastructure is currently vulnerable to climate, a changing climate may further stress the system and thereby decrease energy system reliability and performance.

Most notably, some renewable energy generation technologies are significantly sensitive to climate. For example, hydroelectric generation, which in 1999 accounted for 8% of US electric production and 19% globally, is reliant upon precipitation patterns and temperature-related evaporation from reservoirs. One study of the effects of climate change on the Colorado River Basin projected that a 20% reduction in natural runoff would result in a 60% reduction in power generation (Nash, 1993). Similarly, an analysis of river basins in northern California concluded that with a 20% reduction in precipitation and a 2°C increase in temperature a decrease in hydroelectric generation of, at minimum, 35% could be expected (Munoz, 1998). In countries such as Canada, Brazil and Ghana or regions like the Northwest United States, where a significant share of electricity is supplied by hydroelectric climate change may substantially alter electricity generation. For example, a drought in the 1998 in Ghana resulted in a reduction of 40% in hydroelectric power which, in turn, reverberated throughout the economy (French, 1998). Not only could climate change alter the amount of electricity produced annually by hydroelectric, but also the timing of power generation. In regions dominated by snowmelt, river flows and subsequently hydroelectric generation might increase during the winter months and decrease during the summer months. Given that climate change may alter the availability of this renewable energy source, an understanding of its consequences is critical for evaluating the financial viability of both existing and potential hydropower schemes (Harrison and Whittington, 2002).

Changes in wind patterns and intensities could occur with a changing climate. Segal and colleagues investigate the implications of such changes for wind energy resources in the US using a refined regional climate model to generate wind power climatologies consistent with present and mid-21st century enhanced atmospheric CO_2 levels (Segal et al., 2001). The study results suggest that the majority of the US would experience decreased daily average wind power availability in the range of 0-30%. Even more recent analyses have indicated the “need to consider climate variability and long term climate change in citing wind power facilities” (Breslow and Sailor, 2002). Besides hydroelectric and wind, other renewables that may be impacted by climate change are solar and biomass technologies if the number of sunny days or the growing seasons change, respectively.

Climate change may also affect the performance and reliability of fossil fuel-based energy technologies. While the effects of increased temperature on fossil fuel-based generation units are anticipated to be modest, they occur during times of peak demand because generation efficiency is inversely related to ambient air temperature. For instance, natural gas combined cycle units in New England are 14% less efficient in summer than during the winter, based on a 20-90°F comparison (O'Connor, 2000). Consequently, on hot days when power is needed most to run air conditioners generation plants are operating least efficiently. Compounding the situation, the efficiencies of electric transmission and distribution lines are also inversely related to ambient air temperatures as they exhibit greater resistance with warmer temperatures. As an example, the resistance of aluminum and copper wires increases by approximately 0.4% with each degree centigrade increase between 0°C and 100°C (UNEP, 1998).

In addition to the direct climatic affects on efficiency, fossil fuel plants may be forced to limit their times of operation under future climate change scenarios. For example, the increased frequency and severity of extreme weather events associated with climate change could result in more droughts and thus reduce cooling water availability for fossil fuel based power plants. Just recently a drought in Massachusetts forced local power companies to rely on trucks – up to 30 daily - to transport cooling water to the plant instead of being supplied by the local water company (Russell, 2002). A more widespread or severe drought may have forced the plant to shut down. Similarly, shut downs due to non-attainment of ground-level ozone standards may increase since high temperatures are a precursor to ozone formation.

Today, the majority of power disturbances that affect consumers are a result of adverse weather conditions effecting the transmission and distribution system (EIA, 1995a). Climate change may be an additional stressor on the system and further exacerbate the situation (Eto et al., 2001). The increased frequency of extreme weather events anticipated to accompany climate change could result in more extreme wind events such as tornadoes and hurricanes and extreme precipitation events. Extreme wind events can exceed the design standards of power distribution structures or their components causing collapse or damage, or cause hazards from wind-borne debris.

Lightning may be another weather variable affected by climate change. One study projects that a 4.2°C warming would result in global cloud-to-ground lightning strikes to increase by 72% (Price and Rind, 1993). Likewise, another analysis finds that a 1°C increase in average wet-bulb temperature in the mid-latitudes is associated with a 40% increase in lightning activity (Reeve and Toumi, 1999). In the US, lightning currently cost electric utilities $100 million annually and for one utility – Duke Power - accounts for 90% of power outages during the summer (Keener, 2001).

Other examples of potential extreme events that may become more frequent with climatic change include the massive ice storm in 1998 that crippled the New England and Eastern Canadian regions. Within Canada the resulting power failure affected 3.6 million people – 90% were without power for more than a week – causing an estimated Cdn$3 billion economic loss (Kerry et al., 1999). In Maine, over 400,000 people lost power requiring 23 days for utility workers to fully restore power (Central Maine Power 1998).

The frequency of extreme and sometimes prolonged heat events is also anticipated to increase with climate change. For the electricity sector this may result in higher peak load demands. One study of Toronto finds that a rise in average temperature of 3°C (5.4°F) increases the probability of a 5-day consecutive run over 30°C (86°F) by a factor of eight. The study also finds that a 3°C (5.4°F) average temperature increase would increase mean peak electric demand by 7% and peak electric load standard deviation by 22% (Colombo et al., 1999). The relatively high increase in variability would result in an appreciable increase in peaking units and the number of high-energy consumption days. The results of the study led the authors to conclude that "design considerations for power supply infrastructure and other engineered systems will need to include climate change concerns due to the significant potential impact on consumption" (Colombo et al., 1999, p.2502). Perhaps indicative of things to come one utility - Entergy Corporation - recently abandoned its electricity load prediction software based on 30-year average historic climate variables for software that employed a 10-year average to better reflect the changing regional climatic conditions (Smith, 2000).

The anecdotal evidence presented above suggests that climate change may need to be better incorporated into regional energy planning, especially given long-term nature of energy supply capital.

3.2 Climate Impacts on Energy Demand

Much of societal energy use is to satisfy heating and cooling preferences. In the United States, residential households devote 58% (EIA, 1999), commercial buildings 40% (EIA, 1995b), and industrial facilities 6% (EIA, 2001a) of energy consumption to space-conditioning requirements, not including water heating. As these end-use sectors account for 20%, 16%, and 38% of total US energy demand, respectively, roughly 22% of all end-use energy is directly utilized for space-conditioning purposes (i.e. heating and cooling).

The large share of energy devoted to heating and cooling suggests that climatic variability and change may have real and measurable affects on energy consumption. To illustrate, one study finds that for industrialized nations as a whole a change in mean annual temperature of 1°C would alter energy demand by approximately 10% (McKay and Allsopp, 1980).

In the next sections, I review the literature on the impacts of climate variability (i.e. weather) on energy demand followed by a review of assessments of climate change impacts on energy demand.

3.2.1 Impacts of Weather on Energy Demand

The link between climatic variables and energy demand has been widely documented and utilized to explain energy consumption and to assist energy suppliers with short-term planning (Considine, 2000; Lehman, 1994; Le Comte, 1981; Quayle and Diaz, 1979; Pardo et al., 2002; Warren, 1981; Morris, 1999; Yan, 1998; Lam, 1998; Reddy, 1990).

Utilities typically employ forecasting models that include short-term climatic forecasts along with long-term seasonal demand 'normals' - based on 30-year averages - to project load capacity requirements. At a larger scale, the National Climatic Data Center (NCDC) has created the "Residential Energy Demand Temperature Index" (REDTI) for energy researchers and planners requiring energy demand forecasts at larger geographic scales than utility supply regions. The REDTI is based on population-weighted heating and cooling degree-days. The NCDC estimates that the REDTI explains between 70% and 86% of the variation in seasonal energy use in the continental United States (NCDCa, 2003).

The interest in the influence of weather on energy demand has led to a number of academic papers beginning in the 1970s. The majority of these papers model energy demand as a function of climatological factors using statistical models or engineering-based building simulation models. Both types of energy models are developed using as independent variables either *primitive variables* such as temperature, humidity, solar radiation, and wind speed, or *derived variables* including heating degree-days, cooling degree-days and apparent temperature. The results of most models indicate that the primary weather variable determining energy use is outdoor air temperature in either its primitive and derived forms. Other weather variables such as wind, humidity and precipitation have also been shown in some studies to influence energy demand, however it is generally to a lesser extent.

A number of energy studies assess the influence of climate on electricity use by examining time-series energy and climate data. Le Compte and Warren examine the correlation between national electricity use and weekly population-weighted degree-day totals during the summers of 1977,1978, and 1979 (Le Compte and Warren 1981). Using a linear regression model they find that weekly population-weighted cooling degree-day totals explain 91% of the variance in national electric output in these years. Similarly, Lam statistically investigates the economic and climatic factors that influence residential electricity use in Hong Kong (Lam 1998). In his analysis, electricity use is estimated as a function of household income, household size, electricity price, and cooling degree-days. The results indicate that a 10% rise in cooling degree-day totals is associated with a 2.2% increase in electricity consumption. Lam observes that climatic variables explain between 74% and 93% of seasonal variation in residential electricity consumption. In a statistical study of aggregate electricity demand in Spain, Pardo (2002) employs a stepwise estimation technique as a consequence of serial correlation and the dynamic behavior of climatic variables. The study finds that the current and previous day's cooling degree-day totals are significant factors in explaining electricity use.

Time-series studies have also examined the influence of climate on energy demand for heating services. Warren and LeDuc develop a nine-region model of the United States to assess regional natural gas consumption sensitivity to degree-days and price (Warren and LeDuc1981). The authors find a linear relationship between heating degree-days and natural gas consumption after controlling for the price of natural gas. They conclude that while climate alone does not explain all of the variation in natural gas usage, it is, nevertheless, critical to account for known fluctuations in usage due to climate. In a finer scale study by Lehman and Warren, the authors analyze the correlation between natural gas sales and heating degree-day data for customers of a utility in Ohio over a 20-year period (Lehman and Warren 1994). Their analysis demonstrates that 97% of the variation in natural gas use by the utility's customers is explained by lagged values of heating degree-days. Sailor and colleagues correlate natural gas consumption in the residential and commercial sectors for each of the 50 US states to population-weighted state temperatures (Sailor, 1998). The authors find that the average state-level responses to a 1˚C temperature increase are a 8.1% decrease in residential natural gas consumption and a 5.9% decrease in commercial natural gas consumption. Finally, researchers in Turkey use the degree-day methodology to determine natural gas consumption for residential heating (Sarak and Satman, 2003). The authors are able to verify present demand patterns as well as use the methodology to assess the supply adequacy of planned natural gas pipelines.

Considine uses an econometric model to estimate price, income and weather elasticities of short-run aggregate energy demand (2000). He finds the weather elasticities of energy demand to be significant. For example, the elasticity of residential natural gas with respect to heating degree-days is 0.333 – meaning a 10% increase in heating degree-days is associated with a 3.3% increase in residential natural gas consumption. A report on the weather impacts on energy consumption in The Netherlands uses monthly time series data to investigate the link between weather variability and electricity and natural gas use (Lise, 2000). The analysis suggests only a weak relation between degree-days and monthly electricity, but a strong influence of temperature on natural gas use. An increase in average temperature of 1°C is associated with a 3.8% decrease in natural gas use. A comprehensive study by Quayle and Diaz examines the correlation between heating degree-days and both site-specific electricity and heating oil consumption for individual residences and regional residential electricity consumption (Quayle and Diaz 1979). They conclude that ambient air temperature is the primary element controlling the variability in residential energy use.

Another body of research that investigates the climate-energy link is found in the engineering literature. These studies typically use building energy simulation models to assess the influence of weather on building energy demand as well as on the sizing requirements of heating and cooling systems (for example see Chou and Chang, 1997). Energy simulations models, such as the Department of Energy's (DOE) DOE-2, permit researchers to hold fixed all influences on energy use besides weather. However, they are limited to the analysis of single buildings or generic building types given the requisite detailed inputs such as hourly climate data or type of HVAC equipment.

3.2.2 Climate Change Impacts on Energy Demand

Only recently have researchers begun to investigate the longer-term implications of climatic change for energy use patterns and capital investment decisions. The results of these studies have varied widely depending on model methodology, the current climate of the study area, the scale of the analysis, the timeframe of the analysis, the energy forms investigated (i.e. electricity, natural gas, etc), assumptions about technological change, and assumptions about climatic change. Moreover, all of these studies have modeled energy demand responses based on historic sensitivities to climate variability and consequently have not accounted for potential adaptations to changing climate conditions that might alter the energy demand sensitivity function. While some of the models have accounted for changes in the capital stock, the changes have not been modeled as adaptations to changing climatic conditions.

One of the first studies of climate change assessed the impacts at the national level on the electricity sector in the United States (Linder, 1990). The study found that between 2010 and 2055 climate change could increase electric capacity addition requirements by 14% to 23% relative to non-climate change scenarios, requiring investments of $200-300 billion ($1990). Nordhaus (1991) and Cline (1992), based on the results of Linder's study, report increases in energy expenditure of $0.9 billion and $10.3 billion, respectively, for a 2.5°C warming.

A study by Morrison and Mendelsohn uses micro-data for individuals and firms across all fuels in the U.S. and finds a 2°C increase in average temperature would increase energy expenditures by $6 billion in 2060, whereas a 5°C would increase damages by $30 billion (Morrison and Mendelsohn, 1998). In contrast, a national-level study (Rosenthal et al., 1995) of total energy use indicate global warming would reduce energy use and expenditure. Rosenthal uses an engineering based approach to estimate the change in energy consumption and expenditures required to maintain current internal building temperature assuming the 2010 characteristics of the building stock from the EIA's Annual Energy Outlook 1994. The study finds that a 1°C warming in the U.S. would reduce energy expenditures by $5.5 billion and primary energy use by 0.70% in 2010 relative to a non-warming scenario (Rosenthal et al., 1995).

Research assessing potential climate change impacts on commercial energy use in the U.S. finds, after accounting for change in the building stock, that a 4°C increase in average annual temperature is associated with a 0-5% reduction in commercial energy use in 2030 (Belzer, 1996).

In a national assessment of Israel, Segal et al. estimate an increase in temperature of 4°C is associated with a 10% increase in average summer peak loads (Segal, 1992). In Greece, a 1°C temperature increase is projected to decrease heating energy use by 10% and increase cooling energy use by 28.4%, assuming a business-as-usual scenario (Cartalis, 2001). A study of electricity demand in Finland finds that with temperatures increases of between 1.2°C and 4.6°C, electricity demand would increase by between 7% and 23% (Aittoniemi, 1991).

3.2.2.1 Reasons for Regional Energy Demand Assessments of Climate Change

The majority of studies examining the consequences of climate change for the energy sector, as detailed in the previous section, typically quantify the impacts at a relatively course spatial resolution. As a consequence, they capture only an average response for a large geographic area. However, average responses have little value in guiding place-specific adaptation response to climate change (Wilbanks and Kates, 1999) and may result in the prescription of inappropriate policy recommendations. Therefore, if the objective of a study is not only to quantify impacts but also identify policy solutions, the study should be conducted at a scale where, as the IPCC notes, "the impacts of climate change are felt and responses are implemented" (IPCC, 2001a, p.25).

This dissertation argues that analyses of energy demand sensitivities to climate and climate change should be performed at the regional scale for a number of reasons. The first reason is because of regional differences in energy infrastructures (Boustead, 1994). Regional energy systems differ in terms of energy sources, efficiencies and characteristics of supply and conversion infrastructure, end-use technologies, building thermal characteristics, and end-user preferences. In part, the differences are due to adaptation to climate, as the built end-use infrastructure and housing stock have evolved to service a unique mix of heating and cooling requirements under the relatively stationary historic regional climate regime (Pressman, 1995). As an example, apartment buildings in the cooler Northeast climate are commonly constructed of heat-retaining red brick, are well insulated, and few offer central air-conditioning. The unique attributes of the regional energy infrastructure along with the inherent slow turnover rates of energy technologies suggest policy objectives will be limited in the short run. For instance, changes in building codes implemented today to decrease energy consumption will have little effect on energy consumption in the short run, as is evident by the fact that 82% of homes in the northeast census region were built before 1980 (EIA, 1999).

A second justification for carrying out a regional energy impact assessment is that residential, commercial, and industrial sectors exhibit distinct demand sensitivities to climate. Residential energy end-users are typically the most sensitive to climatic conditions whereas the industrial sector has been found to be relatively insensitive to climate (Lakshmanan, 1980; Sailor, 1997; Sailor, 2001). Therefore, the structure of a local economy significantly influences the sensitivity of regional energy demand to climate since sectoral compositions vary across regions.

A third reason for energy demand sensitivity analysis to be carried out at regional scales is that global climate change is anticipated to have geographically distinct impacts. For example, global climate models predict that the Northeast region of the US will experience among the lowest rates of warming relative to other regions of the country (Barron, 2002). In which case, analyses that apply a uniform temperature increase over entire continents or nations may miss important geographic impacts on energy use. The ability to capture and interpret geographical variations in climate change impacts on energy systems is particularly important for a country like the US with its large geographic extent.

Each of these reasons suggest that for energy sector impact assessments of climate change and the formulation of efficient adaptation policies, analyses need to be formulated at a scale that accounts for place-specific characteristics. Several empirical studies support these arguments for regional assessments of climate impacts on the energy sector rather than national level assessments.

A state-level analysis of residential and commercial sector electricity use observes significantly different variation in demand sensitivities between states with, for example, a 2°C temperature increase associated with an 11.6% *increase* in residential per capita electricity in Florida, but a 7.2% *decrease* in Washington (Sailor, 2001). Even for neighboring states, such as Florida and Louisiana, residential and commercial demand sensitivities are observed to be noticeably different. In two other studies, Sailor and Munoz (1997) estimate the weather sensitivity of electricity and natural gas consumption in eight US states and Sailor and colleagues (1998) correlate natural gas consumption in the residential and commercial sectors for each of the 50 US states to climate variables. Both studies observe a wide range of energy sensitivities to climate variables. Likewise, Warren and LeDuc statistically estimate natural gas consumption to prices and heating degree-days in a nine-region model of the US and find noticeable regional differences (Warren, 1981). Linder and Inglis (quoted in Smith, 1990) project a 1°C temperature change would alter various utility area peak demands in the US by between –1.35% to 5.4%, suggesting significant regional variation. Scott and colleagues (1994) use a building energy simulation model to assess the impacts of climate change on commercial building energy demand in four US cities (Seattle, Minneapolis, Phoenix, and Shreveport). The authors find unique demand responses to climatic changes with, for instance, a 7°F increase in daily temperature increasing cooling energy use in Phoenix by 36.6% whereas Seattle experiences a 93.3% increase (Scott, 1994).

The variations in regional energy demand sensitivities observed by all of these studies suggest regional assessments of energy demand responses to climate change are needed.

3.2.2.2 Reasons for Dynamic Energy Demand Assessments of Climate Change

Past assessments of climate and climate change impacts on energy demand have, in general, modeled energy demand sensitivities to climate as time-invariant functions. These studies typically estimate, using time-series analysis, an average energy demand sensitivity such as the percent change in electricity demand per degree Celsius change in temperature. However, energy demand sensitivities may change over time with changes in other factors, including changes in efficiencies of end use technologies, energy prices, or affluence of the population. In one of only a handful of studies to examine the dynamics of energy demand sensitivities, the sensitivity of peak electric power demand to air temperature was found to have increased by 230% over the 15 years between 1975 and 1990 in Japan (Hattori 1991, quoted in IPCC 2001a). These findings suggest that accounting for the dynamics of energy demand may be critical in assessing future energy demands, with or without climate change.

Moreover, understanding the dynamics of energy demand sensitivity may be important with respect to climate change because of the relation between ambient temperature and the prevalence of air conditioners. A recent study by Sailor and Pavlova (2003) develops a generalized functional relationship between market saturation of air conditioners and cooling degree-days for 39 U.S. cities. Their results indicate that air-conditioning saturation rates in cities that currently have low to moderate saturation may markedly increase with long-term warming, leading the authors to conclude that "the total response of per capita electricity consumption to long-term warming may be much higher than previously thought" (Sailor and Pavlova 2003).

The fact that energy demand sensitivities are dynamic has important implications for projecting energy demand responses to climate change. In this dissertation, I develop energy demand models with and without a dynamic component to assess the extent to which energy demand sensitivities have changed over time and the potential implications of climate change.

4. Research Methods

4.1 Introduction

In this dissertation, I explore the impacts of climate change on energy demand utilizing the impact-adaptation methodological framework. The framework calculates net impacts after accounting for the exposure, sensitivity, and adaptive capacity of the system to changes in climate stimuli. However, because the unit of analysis (energy demand) is indirectly influenced by climate through energy users' preferences for indoor climate rather than direct physical effect (e.g. the effect of temperature on agricultural crop yields), the exposure, sensitivity, and adaptive capacity have slightly different meanings than is customary in the impact-adaptation literature.

The *exposure* of energy demand to climate stimuli is the share of a region's population or employees that possess temperature-sensitive energy using technologies. For example, the exposure of natural gas demand to heating degree-days is based on the share of the population with natural gas furnaces. Some researchers have argued that society is increasingly becoming "climate-proofed" because it is less exposed to climate (Ausubel, 1991). Ironically, any "climate-proofing" that has occurred has generally taken place by increasingly expending energy to control indoor micro-environments. Other economic sectors have, in effect, reduced their exposure to outdoor climate by increasingly relying on the energy sector for space-conditioning services. For example as Schelling asserts "{m}anufacturing rarely depends on climate, and where temperature and humidity used to make a difference, air conditioning has intervened" (Schelling, 1992, p.5).

The *sensitivity* of energy demand to changes in climate is a 'derived' sensitivity because it is individuals and other economic actors demanding energy to reduce their exposure to climate. The sensitivity is the degree to which energy demand for space-conditioning services changes with changes in a climate stimuli (i.e. temperature). In this dissertation, 'energy demand sensitivity' refers to changes in energy demand associated with changes in degree-days. Furthermore, because the focus of this dissertation is on per capita energy demand, the sensitivity encapsulates both the sensitivity and exposure. To illustrate, a state's per capita electricity demand sensitivity to cooling degree-days can increase if either; (1) individuals who currently have air-conditioners use them more intensely (sensitivity), or (2) more people use air-conditioners (exposure).

The *adaptive capacity* of energy demand is the extent to which a region's energy demand sensitivity function can adjust to potential changes in climate. A region's energy demand sensitivity function is a product of the thermal attributes of the building stock (i.e. insulation levels), efficiencies of temperature-sensitive end-use technologies, and behavioral characteristics of energy users. Previous research has modeled energy demand responses to climate change as extrapolations of past sensitivity to prevailing climatic conditions. These types of models portray adaptation as extremely short-sighted, reactive responses occurring entirely at the thermostat. To date, no research into climatic impacts on energy demand has implicitly or explicitly modeled anticipatory adaptation, which would manifest itself in changes in the energy demand sensitivity function to moderate potential increases in energy demand due to climate change.

In this dissertation, I argue that it is critical to understand the adaptive capacity of energy demand now, because the energy sector is capital intensive and, thus, will be slow to react to policy stimuli (Lempert et al., 2002). The long lifetime of the existing capital stock impedes the rate at which energy demand sensitivity functions can be modified to be better calibrated to new climatic conditions. Consequently, climate change may have significant implications for the energy sector because the weather parameters to which the capital is sensitive will likely change significantly during the lifetime of the capital investment (Fankhauser et al., 1999). Therefore, the potential impacts of climate change on the energy sector are important to understand now, in order to develop sound adaptation policies.

4.2 Methodological Approaches for Assessing Sensitivity and Adaptive Capacity

The impact of climate change on any biological or socioeconomic system is a function of the system's exposure, sensitivity and adaptive capacity to climatic stimuli. This study, therefore, employs two distinct methodologies to investigate potential energy demand implications of climate change.

The first methodology, aimed at quantifying the exposure and sensitivity of energy demand to temperature changes, is a temporal analysis. Quantitative estimates of historic temporal relations between energy demand and temperature in individual states and census divisions are developed, which then are used to assess potential energy demand responses to climate scenarios. As this approach employs an econometric analysis, it implicitly assumes that energy users respond to a changing *climate* the same way they have reacted to past changes in *weather*. Energy demand responses to climate change are based solely on historic energy demand sensitivities to temperature variability. Consequently, the approach is limited in its ability to account for potential anticipatory adaptations that might alter the energy-temperature relation beyond the rate and extent that have occurred in the past.

Geographic analysis, the second methodology, is used to provide additional insight beyond that gained by the temporal analysis into the adaptive capacity of energy demands to current climate, and in turn into the potential longer-term effects of climate change on energy demand sensitivity functions. Rather than assessing how energy demand has changed with past changes in *weather* for a specific region, the geographic analysis examines how across regions the energy demand-temperature relationship is different in different *climates*. The differences are assumed to be adaptations to climate and, thus, can be synthesized with the temporal analysis findings to develop potential energy demand responses to climate change that account for both the system's sensitivity and adaptive capacity.

The methodologies used in developing the temporal analysis and geographic analysis are discussed in sections 4.2.1 and 4.2.2, respectively. Section 4.3 details the technique by which the two analyses are synthesized and then combined with climate change scenarios to project energy demand responses.

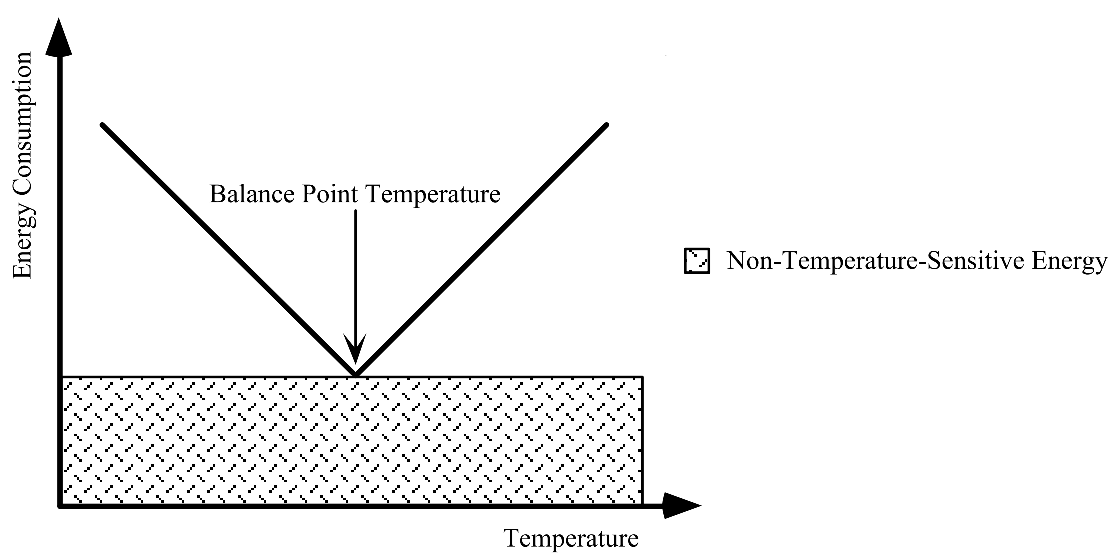
4.2.1 Temporal Analysis Methodology

The temporal analysis statistically assesses energy demand *sensitivities* to degree-days using time-series data. Once the statistical relations are developed they are then used in combination with climate change scenarios to estimate future energy demands. The temporal analysis accounts for demand responses by energy users to climate change scenarios based on how users have reacted in the past to changes in temperature variability. Accordingly, the projected impacts of climate change on energy demands represent business-as-usual (BAU) scenarios and act as a benchmark to assess the desirability of alternative futures, such as those developed with the geographic analysis.

4.2.1.1 Degree-day Formulation

Degree-days are a common energy accounting practice for estimating energy demand in which energy demand is broken down into three components: (1) non-temperature-sensitive energy, (2) heating energy, and (3) cooling energy. The degree-day approach presumes a V-shaped energy demand-temperature relationship (see Figure 5). The temperature corresponding to the bottom of the V-shaped function is that temperature where neither heating nor cooling services are required because outdoor temperature produces the desired indoor temperature. This 'just right' temperature is the *balance point temperature* and represents the amount of energy demanded for purposes other than space-conditioning (non-temperature-sensitive energy load).

Figure 5. Theoretical Relationship between Temperature and Energy Demand.



Energy is required for space-conditioning purposes when outdoor temperature deviates from the balance point temperature. If outdoor temperature is lower than the balance point temperature then energy is required for heating services, whereas if outdoor temperature is higher than the balance point temperature then energy is required for cooling services. Energy consumed in excess of the amount of energy required at the balance point temperature is the temperature-sensitive energy load, which increases in proportion to the absolute temperature difference with the balance point temperature. Accordingly, temperature-sensitive energy use is a function of outdoor temperature, desired indoor temperature and thermal efficiency of the building shell (Eto, 1998). The balance point temperature (T_B) of an individual building is mathematically defined as:

$$T_B = T_S\,(G/L)$$

Where:

T_S = desired or set-point temperature:

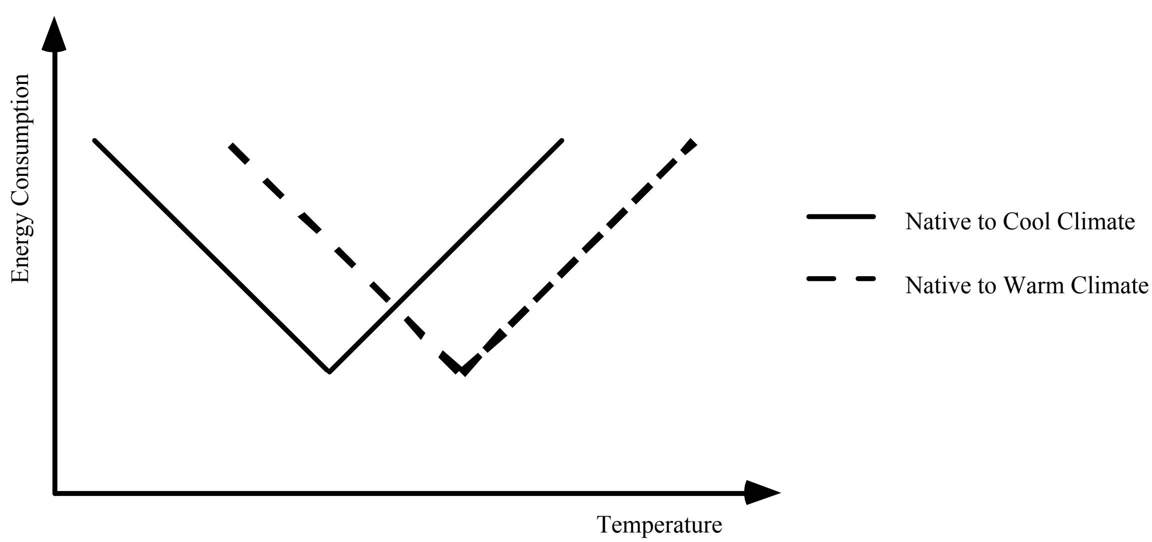
G = internal non-space-conditioning heat gain in watts;

L = building heat loss coefficient in watts per degree.

As is clear from the equation, the balance point increases as (1) the desired internal temperature increases, (2) internal heat gain increases, or (3) the loss coefficient decreases. Therefore, differences in balance point temperature are a result of differences in either desired indoor temperature (a behavioral adaptation to climate) or differences in thermal efficiency of building shells (a technological adaptation to climate). In this dissertation, differences in balance point temperature are discussed as being attributed to differences in thermal efficiency of building shells because research into human standards of thermal comfort indicate a narrow comfort band in technologically and economically areas, such as the US (Meyer, 2002).

Energy use analyses commonly employ a base temperature of 65°F as the balance point and derive heating degree-days and cooling degree-days as absolute temperature differences. However, the actual balance point temperature of energy systems may vary depending on non-temperature weather conditions (e.g. humidity, precipitation, wind), cultural preferences, and the thermal characteristics of the building stock and surrounding environment (Nall, 1979; de Dear, 2001). To illustrate, the balance point temperature observed in a cold climate would be lower than in a warm climate if, all else equal, the cold climate's housing stock is comprised of better insulated homes (see Figure 6). Because energy users have adapted building shell thermal attributes to the regional climate, balance point temperatures tend to gravitate towards the central tendency of the region's temperature regime which is limited, nonetheless, by thermodynamic constraints.

Figure 6. Balance Point Temperatures in Cool and Warm Climates.



Although place-specific variations in balance point temperature exist, most assessments continue to use 65°F as the base temperature, perhaps due to the ease of data collection since degree-days are commonly calculated with the 65°F base. However, using 65°F as a universal base temperature implicitly assumes that the temperature where energy is demanded for heating and cooling services is the same everywhere.

The method used in this dissertation is to tailor the balance point temperature using a quantitative approach. In this way, the functional relationship between energy demand and temperature is optimally specified. Similar to the methodology used by Belzer and colleagues (Belzer, 1996), statistical models for census divisions and states are iteratively run over a range of base temperatures. Each iteration is performed using degree-days formulated with a different base temperature at 1˚F intervals. The base temperature that explains the largest share of changes in energy demand (i.e. producing the highest R-square) is then objectively designated as the balance point temperature for that state or census division. The approach is used for each energy type in each end use sector.

The iterative approach used in this dissertation to determine the balance point explicitly recognizes that 'hot' and 'cold' are relative terms. Based on the balance point temperature, hot and cold are objectively defined as the range of temperatures above or below the temperature where energy is demanded for cooling or heating services, respectively. Hence, it is 'hot' when cooling services are demanded and, conversely, it is 'cold' when heating services are demanded.

One simplifying assumption that was made in order for the iterative procedure to be utilized was that there exists only one 'just right' or balance point temperature for each region. All temperatures below the balance point, therefore, result in some amount of energy required for heating whereas all temperatures above the balance point result in some amount of energy required for cooling.

To reflect the heating and cooling components of space-conditioning energy, degree-days are comprised of heating degree-days (HDD) and cooling degree-days (CDD). Heating degree-days can be thought of as an index of 'coldness', whereas cooling degree-days as an index of 'hotness'. Coldness and hotness are temperature differences from 'just rightness' – as defined by the balance point temperature. In other words, heating degree-days and cooling degree-days are measures of the combined intensity and duration of coldness and hotness, respectively, over a specified time period. Each degree deviation from the balance point temperature is counted as a degree-day. For example, if the balance point temperature is 65°F and the day's average temperature is 50°F this results in 15 heating degree-days for that day. Degree-days can be accumulated over time to give weekly, monthly or annual totals.

The degree-day methodology more accurately estimates temperature-sensitive energy requirements than does outdoor temperature because the relationship between temperature and energy required for heating and cooling involves a threshold and, thus, is non-linear. If, instead of degree-days, energy requirements were estimated as a quadratic function of temperature (i.e. temperature and temperature-squared) then the mathematical specification presumes that heating energy and cooling energy have the same sensitivity to changes in temperature. The degree-day methodology, in contrast, permits the separate estimation of the effects of heating and cooling on energy use because temperature is disaggregated into the derived components of heating degree-days and cooling degree-days (Jager, 1983).

Provided that the degree-days are derived from the appropriate balance point temperature, space-conditioning energy requirements are approximately proportional to degree-days (ASHRAE, 2001). In general, the assumption of a linear relationship between degree-days and energy consumption is more valid for energy consumed to provide heating services than energy consumed to provide cooling services. This is because the efficiencies of natural gas and heating oil furnaces are relatively unaffected by operating temperature and, thus, burning twice as much fuel results in the production of twice as much heat. With electricity used for cooling, on the other hand, the proportionality assumption is only approximately true since air-conditioners become increasingly inefficient as outdoor air temperatures increase.

4.2.1.2 Energy Demand Sensitivity Models

Historic sensitivities of residential and commercial energy demand to climatic variables are econometrically estimated using the degree-day methodology. Industrial energy demand is not examined since previous investigations (Elkhafif, 1996; Sailor, 1997) as well as the preliminary findings of this study show little correlation between industrial energy demand and climatic variables. Statistical estimations of residential and commercial energy demand sensitivities are independently performed because potentially different energy demand-temperature relations exist between end use sectors (Sailor, 2001; Sailor, 1997).

Moreover, residential and commercial sectors' demands for electricity, natural gas and heating oil are separately estimated because each energy type has a unique demand response to changes in degree-days. By analyzing each energy type independently, demand responses may be observed for an individual energy type that may have been obscured at a more aggregate level. For example, warmer temperatures may have an only marginal affect on aggregate energy demand even if the effects on energy demanded for heating services (i.e. natural gas, heating oil) and energy demanded for cooling services (i.e. electricity) are significant, although off-setting. Because energy types are not perfect substitutes for one another and each has its own capital-intensive supply system and end-use technologies it is important to discern the specific impacts on each energy type.

To better isolate the influence of climatic variables on energy demand from socioeconomic factors, the raw energy data are modified to account for demand on a per capita level in the residential sector and a per employee level in the commercial sector. The choice of per employee in the commercial sector rather than, for example, per unit gross state product (GSP) was made because the emphasis in this analysis is on temperature-sensitive energy demand, which is more a function of the number of employees than the value of economic output.

The statistical models were run using STATA software and corrected for first-order serially correlated residuals using the Prais-Winsten (1954) transformed regression estimator. The Prais-Winsten estimator is a generalized least squares estimator. The specifications of the residential and commercial sector statistical models by energy type are as listed below:

Residential:

$\ln(\text{electricity / person}) = \propto + B_1\text{Trend} + B_2\text{HDD} + B_3\text{CDD} + B_4\text{Light} + B_5\ln(\text{Price}) + \mu$

$\ln(\text{natural gas / person}) = \propto + B_1\text{Trend} + B_2\text{HDD} + B_3\text{Light} + B_4\ln(\text{Price}) + \mu$

$\ln(\text{heating oil / person}) = \propto + B_1\text{Trend} + B_2\text{HDD} + B_3\text{Light} + B_4\ln(\text{Price}) + \mu$

Commercial:

$\ln(\text{electricity / employee}) = \propto + B_1\text{Trend} + B_2\text{HDD} + B_3\text{CDD} + B_4\text{Light} + B_5\ln(\text{Price}) + \mu$

$\ln(\text{natural gas / employee}) = \propto + B_1\text{Trend} + B_2\text{HDD} + B_3\text{Light} + B_4\ln(\text{Price}) + \mu$

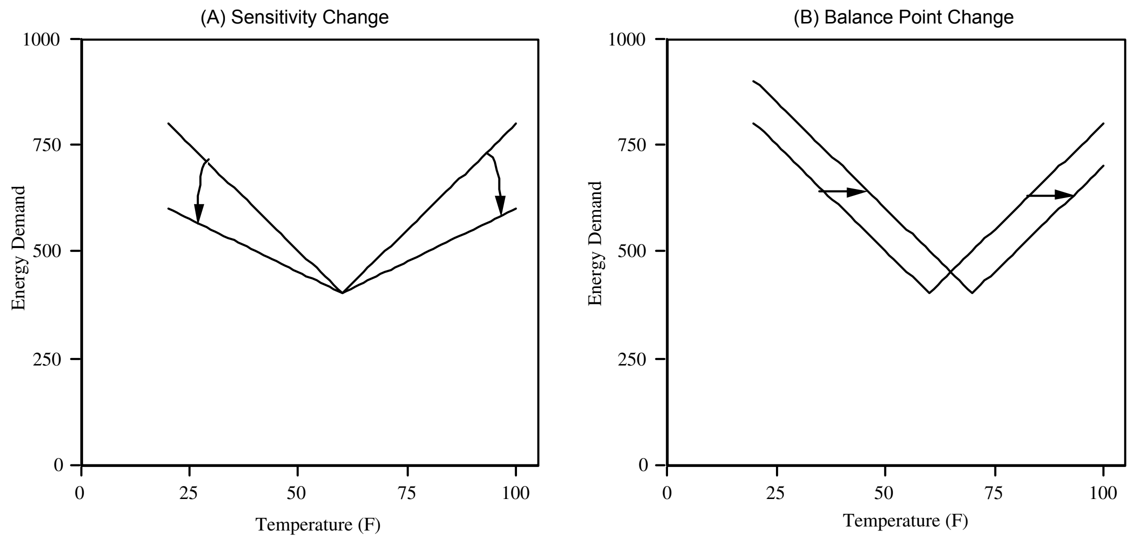
The dependent variable (energy demand) in each energy demand model is specified in the natural log format. The output coefficients on the independent variables, therefore, represent the percent change in energy demand associated with a unit change in that independent variable. The constant term ($\propto$) indicate the level of non-temperature sensitive energy demand. The trend variable represents the average annual percent change in non-temperature sensitive energy demand over the period of analysis. The output coefficients on the HDD and CDD variables indicate percent changes, respectively, in heating and cooling energy demand associated with changes in heating degree-days and cooling degree-days. The light variable indicates the percent change in energy demand associated with a one hour change in daylight. The price of energy variable, which itself is expressed in the natural log format, represents the percent change in energy demand associated with a percent change in the price of energy (i.e. price elasticity of energy demand). Contained in Appendix I are figures that illustrate the following independent variables: constant, annual trend, HDD, and CDD as well as the balance point temperature. A description of the independent variables and rationale for their inclusion in the models is provided in section 5.1 and the results of these models are presented in section 6.1.

In addition to the statistical models described above, alternative residential and commercial sector models that include dynamic degree-day sensitivity variables are developed for each energy type. The dynamic sensitivity variables capture potential time-varying components of energy demand sensitivities to changes in degree-days over the period of analysis. For example, with the increasing penetration of air-conditioning into buildings it is expected that the sensitivity of electricity to cooling degree-days would increase. Dynamic sensitivity variables are the multiplicative product of degree-days variables and the annual trend variable and represent the average annual change in demand sensitivity. The results of the residential and commercial energy models with dynamic sensitivity variables are presented in section 6.2.

4.2.2 Geographic Analysis Methodology

A region's energy demand sensitivity function (i.e. V-shaped energy demand-temperature relation) is defined by the efficiencies of space-conditioning technologies, thermal attributes of building shells, and societal behavioral patterns. To illustrate, the V-shaped energy profile is flatter in regions that have lower energy demand sensitivities to hot and cold temperatures (see Figure 7a). Likewise, the energy profile is to the right in regions where the thermal attributes of the built environment are designed for warmer climates or where a society has a preference for higher indoor temperatures (see Figure 7b).

Figure 7. Determinants of Regional Energy Demand Sensitivity Functions.



The technological and societal factors that determine a region's energy demand sensitivity function all arose in the context of a distinct climate regime, whose characteristics were assumed to be stable. If, as is a thesis of this dissertation, energy users have adapted to effectively meet space-conditioning desires under current climatic conditions, then climatic change may induce further adaptation to the new climatic characteristics. Such adaptation could include changes in building attributes, space-conditioning technologies, and behavioral patterns significantly different from those observed over the historical record. Any of these adaptations would, in turn, alter the shape of the V-shaped energy demand sensitivity function in a way that moderates the impacts of climate change on energy expenditure. Consequently, understanding climatic change-induced modifications of the energy demand sensitivity function is essential in accurately projecting long-term energy demand responses to climate change. Therefore, this study attempts to develop a metric of adaptation, which can then be incorporated into energy demand responses to climate change scenarios.

A geographic analysis methodology is developed to discern levels of adaptation to current climate and to infer the *adaptive capacity* of energy demand to climate change. The geographic analysis compares variation in states' energy demand sensitivity functions developed in the temporal analysis because, as is a hypothesis of this dissertation, built into energy demand sensitivities to temperature variability are energy users' adaptations to prevailing climatic conditions. In examining this hypothesis, the states, whose energy demand profiles are investigated, are on a north-south orientation – spanning from Maine to Florida – to maximize differences in climate and presumably the level of adaptation to climate. In this study, adaptation to climate is examined using balance point temperature.

States' population-weighted average temperatures are statistically correlated with the balance point temperatures of electricity, natural gas, and heating oil produced in the temporal analysis. Observed correlation between balance point temperatures and population-weighted average temperatures quantitatively reflects the level of adaptation by energy users to climate. The correlation is then, in turn, used to endogenously specify future balance point temperature in projections of energy demand responses to climate change. In this way, adaptation to climate change is modeled by altering the balance point temperature of an energy system to the resultant temperature change of the climate change scenario. In effect, the adaptation in balance point temperature is a redefinition of 'hot' and 'cold' for a region.

The geographic analysis is similar to the use of spatial analogues that, as the IPCC notes, are "valuable for validating the extrapolation of impact models by providing information on the response of systems to climatic conditions falling outside the range currently experienced at a study location" (IPCC, 2001a). However, the use of spatial analogues is limited because: (1) there may exist a lack of correspondence between characteristics (climatic and non-climatic) of a study area and its spatial analogue, and (2) it compares equilibrium situations and, therefore, does not account for the process of adaptation nor its associated costs (Tol, 1998).

The geographic analysis complements the temporal analysis by providing alternative future energy profiles that are possible with climate change for a region, but that differ with responses observed in the past or with responses derived from past trends.

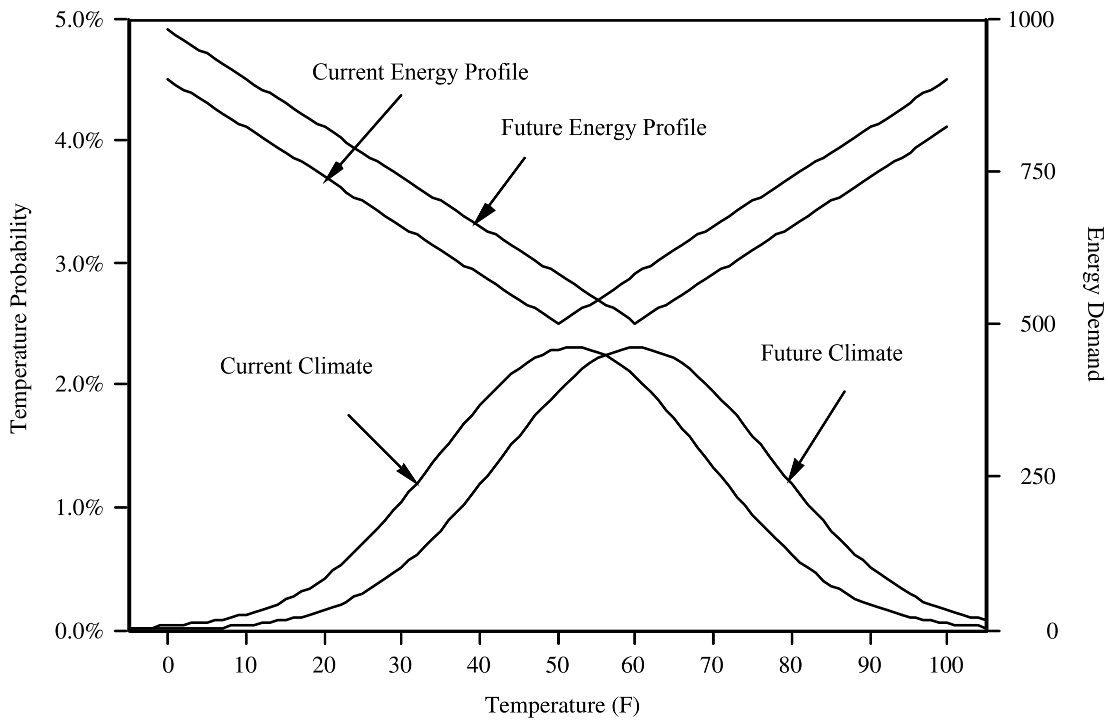
4.3 Development and Application of Climate Scenarios to Energy Demand Responses

To assess energy demand responses to changes in temperature and degree-days the study employs incremental scenarios of climate change. Incremental scenario analysis is a simulation technique where "particular climatic (or related) elements are changed incrementally by plausible though arbitrary amounts (e.g. +1, +2, +3, +4˚C change in temperature)" (IPCC, 2001a). For the present research, scenarios of future monthly temperature for each state and census division are created using changes in temperature of +2˚F and +4˚F in combination with the current climatic normals. The temperature changes are uniformly applied to each month of the year. Based on the changes in monthly temperature, degree-days are estimated using the Thom methodology (see Section 5.1.1.2) to produce degree-days for each climate scenario. The historic standard deviations of monthly temperature that were used to produce the historic degree-day estimates are also used to produce the projections of degree-days under the climate scenarios.

Energy demand responses to the incremental climate change scenarios are constructed using the temporal analysis and a synthesis of the temporal analysis and the geographic analysis. The energy demand responses based on the temporal analysis assess the future energy implications of climatic change using a statistical estimation technique that implicitly assumes a continuation of past trends. In essence, the temporal analysis superimposes a new climate regime on the current energy demand-temperature profile in order to estimate the energy implications of climatic change (refer to Figure 8). Consequently, the results represent future energy responses to climate change under a business-as-usual (BAU) scenario. Energy demand responses to climate scenarios based on the temporal analysis are presented in section 7.1.

Energy demand responses to climate scenarios based on the synthesis of the temporal analysis and the geographic analysis use the sensitivity from the temporal analysis and balance point temperature from the geographic analysis. Consequently, the energy implications of climatic change are simulated using a new energy profile that reflects changes attributable to longer-term adaptation to new climate characteristics (refer to Figure 8). In this case, the balance point temperature component of an energy profile is modified based on the degree of change in the incremental scenario of climate change. Put another way, the approach retains the region's sensitivities to 'hotness' and 'coldness', but redefines 'hot' and 'cold' by calculating degree-days from a new balance point temperature. Energy demand responses based on the synthesis of the temporal analysis and the geographic analysis are presented in section 7.2.

Figure 8. Current and Potential Future Energy Profiles and Temperature Distributions.



5. Data, Regional Background Characteristics, and Historic Energy Demand Profiles

5.1 Data

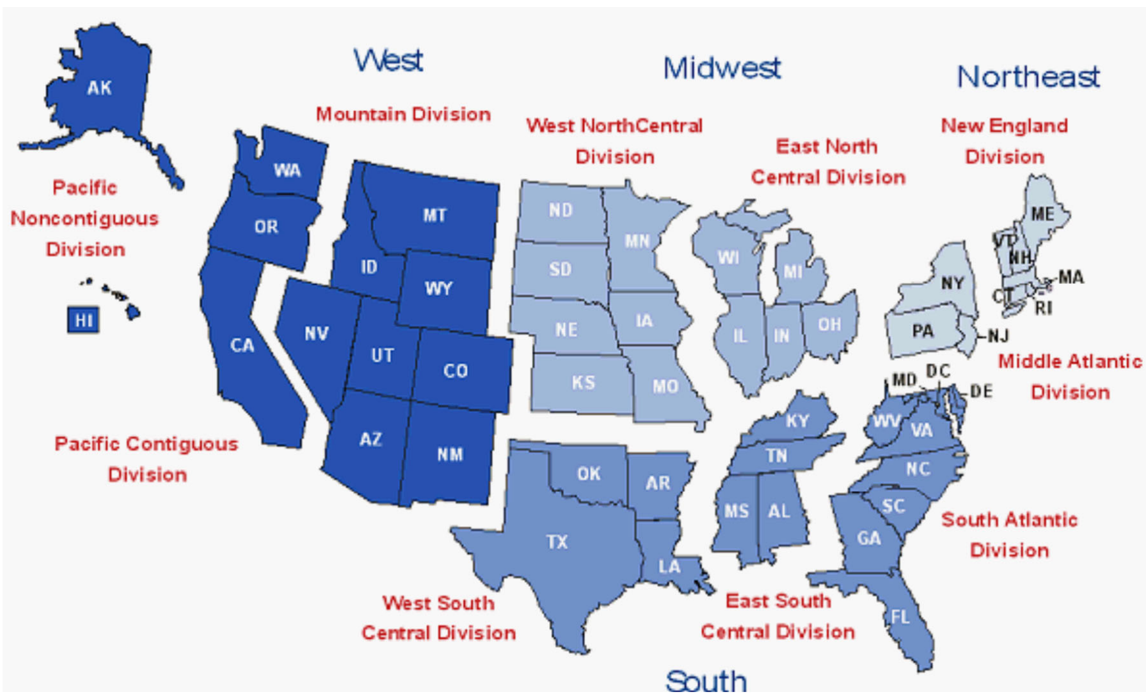
Climate, energy and socio-economic data for this study have been collected in a uniform fashion for the seventeen states in the New England, Middle Atlantic and South Atlantic census divisions. All data has been collected as, or extrapolated to, monthly intervals. This study uses monthly time-series data rather than annual data because data on a monthly interval produces more robust estimates of the energy-climate relationship as there are more observations and variability between observations. While not investigated in this study, the use of monthly data allows for the assessment of non-uniform seasonal climatic changes. For example, global climate models predict higher latitude regions will experience a more pronounced warming during the winter season than in other seasons of the year (Greco et al., 1994). The following sub-sections describe the climate, energy, and socio-economic data used in this study.

5.1.1 Climate Data

5.1.1.1 Temperature Data

Energy is not homogeneously consumed over a geographic area. Energy, particularly temperature-sensitive energy, is largely consumed in populated areas and, thus, is related to both weather and population density (Guttman, 1983; Downtown et al., 1988). Consequently, in assessing energy demand over a geographic area, population-weighted temperature better reflects the energy needs of a population than does area-weighted temperature since it is an indication of the temperature perceived by energy end users. Therefore, the present study constructs monthly population-weighted temperatures for each state in the New England, Middle Atlantic and South Atlantic census divisions as well as the census divisions themselves (refer to Figure 9).

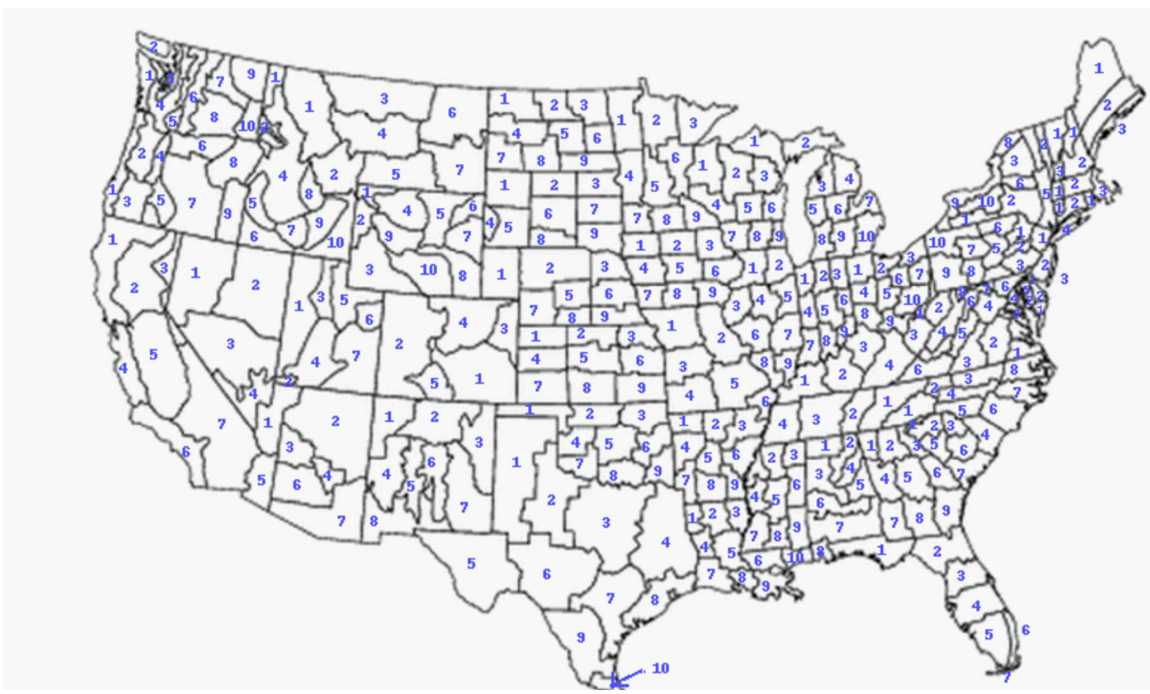
Figure 9. Census Regions and Divisions of the United States.



To compute a state's population-weighted temperature, sequential area-weighted temperatures of climate divisions were obtained from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA) (NCDC, 2003b). A climate division is defined by NCDC as a "region within a state that is as climatically homogeneous as possible" and constructed in a way to often coincide with county boundaries and cover the total area of the state (NCDC 2003b; Guttman 1996).

Within the conterminous U.S. there are 344 climate divisions as depicted in Figure 10. For states under investigation in the present study, the number of climate divisions ranged from one in Rhode Island to ten in New York and Pennsylvania. NCDC derives sequential monthly divisional average temperature series by giving equal weight to all weather stations reporting temperature and precipitation within a climate division. In each climate division there are typically between 10 and 50 weather stations. The divisional temperature data have also been adjusted by NCDC to account for differences in the time of temperature observation between weather stations (Karl et al., 1986).

Figure 10. Climate Divisions in the United States (NCDC, 2003b)



In this study, the area-weighted climate divisional temperatures within a state are weighted by population estimates for each climate division as published in the 2000 U.S. census to ascertain a population-weighted state temperature. The derived estimates of state population-weighted temperature should be relatively accurate given that temperature within climate divisions are, at least theoretically, uniform since the system boundaries of the climate divisions themselves are based on climate characteristics. Consequently, even if the population within a climate division is not uniformly distributed, individuals would still perceive a similar temperature and, therefore, *within* a climate division area-weighted temperature should be similar to population-weighted temperature.

Differences between state population-weighted and area-weighted temperatures are greatest in states with both heterogeneous climates and heterogeneous population densities. For example, the majority of Maine's population lives in the southern part of the state along the coast, where the ocean is able to moderate the cold winter temperatures. New York is similar with most of the population in the southern portion of the state. On average, over the 1977 to 2002 period, monthly population-weighted temperatures in Maine and New York are 2.5ºF and 4.4ºF higher than area-weighted temperature, respectively.

Sequential monthly population-weighted standard deviations of temperature for each state are also computed. Each climate division's standard deviation over the 1971-2000 time period (NCDC, 2003b) is weighted by that climate division's fraction of the state's population to obtain a state-level total. The number of climate divisions in each state as well as a state's mean monthly population-weighted temperature and mean monthly population-weighted temperature standard deviation over the 1971 to 2000 period are listed in Table 2.

The population-weighted temperatures and temperature standard deviations for census divisions (New England, Middle Atlantic, and South Atlantic) are calculated in the same fashion as the state-level temperature and standard deviation. In constructing the population-weighted census divisional temperature, the fraction of each state's population relative to the overall census division's population are used to weight the state's population-weighted temperature. The number of states and climate divisions in each census division as well as the census division's mean monthly population-weighted temperature and mean monthly population-weighted temperature standard deviation over the 1971 to 2000 period are listed in Table 3.

Table 2. States' Population-weighted Monthly Temperatures and Standard Deviations.

	ME	NH	VT	MA	CT	RI	NY	NJ	PA	DE	MD	VA	WV	NC	SC	GA	FL
Number of Climate Divisions	3	2	3	3	3	1	10	3	10	2	8	6	6	8	7	9	7
Mean Temperature (ºF)	43.7	45.2	43.5	48.7	50.0	50.3	50.0	52.2	50.6	55.0	54.6	55.6	52.6	59.1	62.2	61.8	72.5
Mean Standard Deviation	17.0	17.0	17.8	15.7	15.8	14.8	16.1	15.6	15.9	15.5	15.6	14.7	15.1	13.6	13.1	12.9	7.9

Table 3. Census Divisions' Population-weighted Monthly Temperatures and Standard Deviations.

	New England	Middle Atlantic	South Atlantic
Number of States	6	3	8
Number of Climate Divisions	15	23	51
Mean Temperature (ºF)	48.2	50.6	62.2
Mean Standard Deviation	16.0	15.9	12.3

5.1.1.2 Degree-day Data

Degree-days are daily or accumulated daily (weekly, monthly, annual) temperature differences from a predefined base temperature. Heating degree-days (HDD) are commonly defined as the difference or accumulated daily absolute difference between 65ºF and daily temperatures below 65ºF, whereas cooling degree-days (CDD) are the difference or accumulated daily difference between daily temperatures above 65ºF and 65ºF. For first order weather stations, where daily weather sets are largely devoid of missing values, monthly degree-day totals can be derived directly from daily values. HDD and CDD are monthly totals of heating and cooling degree-day variables defined by:

$$HDD = \sum_{d=1}^{N_d} (1 - \gamma_d)(T_b - T)$$

and

$$CDD = \sum_{d=1}^{N_d} (\gamma_d)(T - T_b).$$

In these equations N_d is the number of days in a particular month and T is the average daily temperature ((high temperature + low temperature)/2). The binary multiplier γ_d takes on a value of 1 if the daily average temperature is higher than the base temperature (T_b), and zero otherwise.

When calculating degree-days for geographic areas or stations with incomplete daily temperature series an estimation procedure is required. For example, estimates of monthly degree-days with a base temperature of 65ºF for U.S. climate divisions are published by the NCDC (NCDC, 2003b). NCDC uses a modification of the rational conversion technique developed by Thom to estimate monthly totals (1954, 1960). The original Thom methodology uses average monthly temperature and the standard deviation of the temperature as input variables. The modification involves using a spline-fit of the monthly mean temperatures and standard deviations and, thereby, improves consistency of the estimated degree-day totals by eliminating month-by-month 'steps' in the inputs. NCDC computes degree-day state totals by weighting divisional degree-day estimates by the population in each division to give state-level degree-day totals.

As a major hypothesis of the present study is that balance point temperatures are place-specific, estimates of state monthly degree-days to various base temperatures, rather than maintaining the 65ºF base, are required. In estimating state degree-days to various base temperatures, this study uses the estimation procedure developed by Thom (1954, 1960). The Thom methodology allows the adjusted mean temperatures along with their standard deviations to be converted to degree-days with uniform consistency. The monthly degree-day totals account for the number of days in each month including changes during leap years.

The mean monthly standard deviation along with the population-weighted monthly temperature in each month over the 1977 to 2001 period are used to estimate historic sequential heating and cooling degree-days to base temperatures covering the 45°F to 85°F range at 1°F intervals. In contrast to NCDC's methodology, in this study state-level population-weighted temperatures are derived and used to estimate degree-days rather than estimating degree-days at the climate divisional level and then weighting them by population to ascertain population-weighted totals. Degree-days for census divisions (New England, Middle Atlantic, and South Atlantic) are the population-weighted averages of the state totals.

5.1.2 Daylight Hours Data

Daylight hours, which differ temporally and geographically, are an important factor in explaining energy demand because at the onset of darkness individuals are more likely to turn on lights and to be inside using energy consuming devices. If daylight hours are not controlled for when estimating energy demand, in particular electricity demand, then the statistical findings of energy demand sensitivities to temperature changes will likely be upwardly biased because daylight hours are correlated with monthly temperature. The inclusion of daylight hours in the statistical model, therefore, enables more robust estimates of energy demand sensitivities to degree-days.

As proxies for the hours of daylight in each month in each state the present study uses the hours of daylight in each state's capital city on the fifteenth day of each month. The longitude and latitude of each state capital (Geographic Encyclopedia of PlacesNamed.com, 2003) provided the geographic coordinates of each city. The calculation of daylight hours - the number of hours between sunrise and sunset - are calculated using NOAA's 'Sunrise/Sunset Calculator' (NOAA Surface Radiation Research Branch, 2003).

5.1.3 Energy Data

All energy data is from the U.S. Energy Information Administration (EIA). Monthly sales and price of electricity to residential and commercial end users are from the *Electric Power Monthly* (EIA, various years). The state-level electricity sales data (million kWh) span from January 1977 to December 2001 while electricity price data is limited to the January 1990 to December 2001 period. State-level residential and commercial sectors' electricity use exhibit an upward trend as a result of changes in the size of the population combined with changes in household sizes, building stock and increased proliferation of electric heating and air-conditioning, as well as increases in overall economic activity in the state. Prices of electricity demonstrate intra-annual oscillation but, in general, no inter-annual trend. To adjust for inflation the state's electricity prices are deflated with the Bureau of Labor Statistics' consumer price index for electricity in the respective census region (U.S. Bureau of Labor Statistics, 2003).

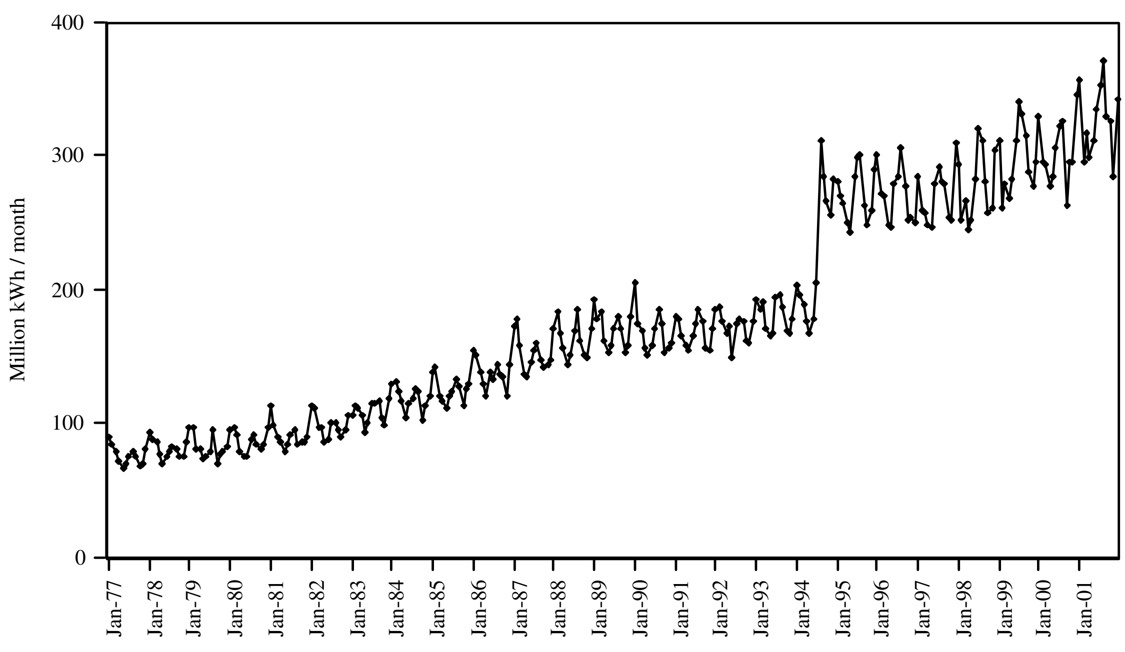
State monthly natural gas sales (MMcf) to residential and commercial end users are from the *Natural Gas Monthly* (EIA, various years). Natural gas sales and price data for the residential and commercial sectors span from January 1984 to December 2001. State natural gas price data series are deflated with the Bureau of Labor Statistics' consumer price index for fuels in the census region (U.S. Bureau of Labor Statistics, 2003).

Monthly sales/deliveries (thousand gallons/day) by prime supplier of heating oil (distillate fuel oil No. 2) to all end users are published in the *Petroleum Marketing Monthly* (EIA, various years). The data are converted to monthly totals by multiplying the average sales per day in each month by the number of days in each month. Due to the fact that sales to specific end use sectors are not available and that the majority of heating oil is consumed by the residential sector, it is assumed that all heating fuel sales are to residential end users. The heating oil sales and price data cover the January 1983 to

December 2001 period. The state prices of heating oil are adjusted for inflation using the Bureau of Labor Statistics' consumer price index for fuels in the census region (U.S. Bureau of Labor Statistics, 2003).

Discrete breaks in the data exist for a number of the state energy data series as complied by the EIA. For example, as shown in Figure 11 commercial electricity sales in New Hampshire suddenly jumps up to a higher level in January of 1995. Were such breaks exist, dummy variables are created to account for the sudden changes in energy use. The dummy variables are coded zero from the beginning of the time series until the data break and 1 afterwards. The data breaks are most often present in the commercial sector, rather than the residential sector, since they are generally due to a re-classification of energy end users from the industrial sector to the commercial sector or vice versa.

Figure 11. Sales of Electricity to Commercial End Users in New Hampshire, 1977-2002.



5.1.4 Socio-economic Data

Annual state population estimates for July of each year are from the U.S. Census Bureau (U.S. Census, 2001). Employment data by industry are from the U.S. Bureau of Economic Analysis (BEA, 2001). Commercial employment data were extracted from the overall employment data based on the commercial enterprises that compose commercial energy use as defined in the *State Energy Report 1999* (EIA, 2000). Both the annual population and commercial employment data are linearly interpolated to obtain monthly estimates such that they coincide with the time-step of the monthly climate and energy data series.

5.2 Regional Characteristics of Residential Dwellings and Commercial Buildings

Geographic differences in the amount of energy used for heating and cooling exist not only due to differences in regional climates, but also due to differences in the physical characteristics of the space-conditioning systems being utilized along with the socioeconomic status and behavioral characteristics of energy users. For instance, energy efficiencies of heating and cooling systems as well as the thermal characteristics of the buildings exhibit marked differences in various parts of the United States. To some degree, such differences in space-conditioning systems are adaptations to regional climatic conditions. By way of example, the South Atlantic's large share of homes with central air-conditioning is an adaptive response to the need for space-cooling services throughout much of the year.

This chapter provides a geographic profile of households, housing units, and space-conditioning systems by census division that are relevant to understanding place-specific energy demand responses to climate but are not included in the quantitative analysis because of data limitations[1]. The ultimate aim of this chapter is to enable the reader a clearer interpretation of the statistical results by providing an overview of the unique regional characteristics that influence the temperature-sensitivity of energy demand. Due to these unique regional characteristics, per capita statistical results can not be compared on an apples-to-apples basis. For instance, when comparing the per capita sensitivity of New England's and the South Atlantic's electricity demand to cold temperatures the prior knowledge that less than 10% of households in New England heat with electricity compared to the majority of households in the South Atlantic is useful for interpreting the results. With such prior knowledge the reader might expect per capita electricity demand to be rather insensitive to cold temperatures in New England, but be sensitive to cold temperatures in the South Atlantic.

The data presented in this section are drawn from two separate surveys conducted by the EIA: the "Residential Energy Consumption Survey" (RECS) and the "Commercial Building Energy Consumption Survey" (CBECS). As the EIA notes, limitations in survey sample size permit for state profiles of only a few of the largest states in the US. Consequently, the residential and commercial energy profiles for this research are presented at the census divisional level and, thereby, offer a general representation of housing units and commercial buildings for the states in each of the three census divisions on the eastern seaboard of the US.

[1] For example, the statistics discussed in this chapter are only available at four-year intervals whereas the quantitative analysis uses monthly time-series data.

5.2.1 Regional Characteristics of Residential Dwellings

Along the eastern seaboard of the US, the Middle Atlantic census division is the most heavily urbanized, with 96.3% of housing units in either city or suburban environments (see Table 4). The Middle Atlantic's relatively high population density combined with the subsequent land scarcity necessitates a larger share of multifamily housing units, such as apartment buildings. Multifamily housing units are approximately twice as prevalent in the Middle Atlantic (22%) as opposed to New England (12%) and the South Atlantic (13%). From a heating energy perspective, multifamily housing units reduce the surface area of housing units and, in turn, increase thermal efficiency. Previous studies have observed that population density and urban form play important roles in determining energy use (Guttman 1983; Lariviere and Lafrance, 1999; Stone and Rodgers 2001; Steemers, 2003). Moreover, as multifamily housing units are generally rented and not owner-occupied there is less of an incentive for the occupants to conserve space-conditioning energy, since heating and cooling energy costs are often included in rental fees.

In contrast to the Middle Atlantic, a significantly larger percentage of housing units in New England (18%) and the South Atlantic (24%) are located in rural areas, typically owner-occupied single-family units. Home ownership rates and the share of single-family detached homes are highest in the South Atlantic followed by New England and then the Middle Atlantic.

Table 4. Housing Unit Characteristics by Census Division.

	New England	Middle Atlantic	South Atlantic
Metropolitan Statistical Area			
Central City………………….	30.1%	32.9%	31.6%
Suburban………………………	51.6%	63.4%	44.9%
Rural…………………………...	18.4%	3.8%	23.5%
Type of Housing Unit			
Single-family Detached Homes..	56.7%	45.3%	61%
Multifamily (5 or more units)….	11.8%	22.0%	12.7%
Ownership of Unit			
Owned…………………………...	64.9%	63.7%	69.3%
Rented…………………………..	35.1%	36.3%	30.7%
Year of Construction			
Homes built before 1960………..	57.9%	56.6%	23.2%
Homes built after 1989………….	6.1%	7.1%	19.8%
Total Number of Rooms (excluding bathrooms)			
3 or less…………………………	11.2%	14.5%	6.5%
4 to 7……………………………	71.1%	68.8%	76.0%
8 or more………………………	17.8%	16.7%	17.5%

Source: 2001b Residential Energy Consumption Survey, EIA.

The average housing unit in New England or Middle Atlantic is older than the South Atlantic with the majority built prior to 1960. New homes are relatively rare in the two regions in part due to their relatively low population growth rates, which negates the need for an expanding housing stock. In contrast, the age distribution of housing units in the South Atlantic is skewed more towards recently built homes given the later settlement of the region as well as recent high regional population growth rates, which create a robust demand for new housing units. In general, new housing units are more likely to be built to stricter building codes and have advanced energy-saving technologies.

The average size of housing units in the US, as measured by the number of rooms, has been increasing over time, which subsequently has increased the demand for space-conditioning services. For example, in the US the percentage of larger housing units, those with seven or more rooms, increased from 22% in 1978 to 29% in 1997 (EIA, 1999). Not surprisingly, the stock of housing units in the South Atlantic are on average larger - with less than 7% having fewer than three rooms - given that they are on average newer.

Households in New England and Middle Atlantic are more frequently comprised of one or two individuals than in the South Atlantic (see Table 5). Conversely, a household in the South Atlantic is more likely, at 42% of the time, to be composed of three or more individuals as compared to New England and Middle Atlantic at 37% of the time. Household incomes in New England are higher and poverty rates lower than in the Middle Atlantic or South Atlantic census divisions. The age distribution of householders in New England and South Atlantic are similar, whereas householders in the Middle Atlantic are skewed more towards higher age brackets.

Table 5. Household Characteristics by Census Division.

	New England	Middle Atlantic	South Atlantic
Household Size			
1 Person………………………..	29.2%	29.5%	24.4%
2 Persons……………………….	33.6%	33.4%	32.9%
3 to 4 Persons…………………..	30.7%	27.2%	34.0%
5 or More Persons……………...	6.4%	9.8%	8.6%
2001 Household Income			
Less than $15,000……………....	14.0%	17.3%	17.5%
$15,000 to $49,999……………..	44.2%	45.0%	44.8%
$50,000 or more………………..	41.8%	37.6%	37.7%
Below Poverty Line			
125%………………………….	14.1%	18.7%	18.8%
Age of Householder			
Under 34 Years………………...	20.7%	15.3%	21.5%
35 to 59 years…………………..	49.8%	44.2%	49.0%
60 Years or Over……………….	27.8%	35.7%	27.7%

Source: 2001b Residential Energy Consumption Survey, EIA.

Residential energy used for space heating purposes represents more than 60% of the energy consumed by housing units in New England and Middle Atlantic as opposed to 36% in the South Atlantic (see Table 6). In New England, heating oil is the most frequently used (50%) main heating fuel, followed by natural gas (35%), and then electricity (9%). Households in the Middle Atlantic predominantly use natural gas (59%) as a main heating fuel because of the density of housing units and general availability of piped natural gas. In the South Atlantic, where heating is relatively less needed, residential heating is most often performed by electricity (55%) because of the low capital costs and high operating costs of electric space-heating.

The amount of heated square footage per home in the two more northern census divisions is considerably larger than in the South Atlantic, especially given their smaller housing unit sizes. Corresponding to the age distribution of housing unit stock in each census division, is the age distribution of the heating equipment. In the South Atlantic heating equipment is much newer with 54% less than 10 years old, whereas in New England and the Middle Atlantic only 32% and 33%, respectively, are less than 10 years old. The newer heating equipment in the South Atlantic is likely more efficient.

Table 6. Space Heating Energy Characteristics of Housing Units by Census Division.

	New England	Middle Atlantic	South Atlantic
Share of energy used for heating	66%	61%	36%
Main heating fuel			
Natural Gas…………………………	34.7%	58.8%	32.5%
Heating Oil…………………………	49.8%	24.5%	3.8%
Electricity…………………………..	8.6%	12.6%	55.2%
Heated square footage per home	1,744	1,743	1,640
Age of main heating equipment			
Less than 10 years…………………..	31.5%	31.3%	54.2%
More than 20 years………………….	29.6%	29.3%	13.4%

Source: Residential Energy Consumption Survey, (EIA 2001b; EIA 1997).

Significantly less energy is consumed for cooling than for heating purposes in all three census divisions (see Table 7). The share of energy used for cooling in New England and Middle Atlantic is marginal, whereas 10% of energy in the South Atlantic is used for space-cooling purposes. Air-conditioners are present in 58% of New England households, 75% of Middle Atlantic households and 95% of South Atlantic households. However, in both New England and the Middle Atlantic the majority of air-conditioners are individual room units, whereas in the South Atlantic the majority are central air-conditioning systems. Additionally, within each housing unit in the South Atlantic air-conditioning is more ubiquitous with 79% of homes air-conditioning the entire house, while in the Middle Atlantic and New England the shares stand at 54% and 33%, respectively. Correspondingly, the amount of cooled square footage per household is highest in the South Atlantic, followed by the Middle Atlantic, and then New England. Over half of homes in New England and South Atlantic have trees providing shade to lessen air-conditioning needs in contrast to only 40% in the more urbanized Middle Atlantic.

Table 7. Space Cooling Energy Characteristics of Housing Units by Census Division.

	New England	**Middle Atlantic**	**South Atlantic**
Share of energy used for cooling	0.005%	1.2%	10%
Share of electricity used for cooling	2.6%	5.5%	16.9%
Homes with air-conditioners	58.4%	74.5%	95.0%
Central…………………………………	14.1%	33.1%	78.9%
Individual Room Units………………...	44.2%	41.4%	14.7%
Rooms cooled in homes with AC			
100%………………………………..….	32.8%	53.9%	79.2%
Less than 50%……………………..…..	39.5%	27.2%	5.8%
Cooled square footage per home	1,070	1,323	1,496
Large Tree(s) that shade the home			
Yes……………………….……………....	50.4%	40.8%	50.3%

Source: Residential Energy Consumption Survey, (EIA 2001b).

5.2.2 Regional Characteristics of Commercial Building

Commercial building energy use is significantly influenced by the type of building activity. For example, office buildings use only 30% of total site energy for space heating, but educational buildings use 54% of energy for space heating (EIA, 1999). The composition of building activities in a region, therefore, affects commercial energy consumption. Building activities in New England are likely to be more sensitive to climatic conditions as two of the region's top three building activities - office and education - require considerable space-conditioning services (see Table 8). In the Middle Atlantic and South Atlantic, building activities more often involve warehouse and storage activities, which demand less space-conditioning services.

Table 8. Commercial Building Characteristics by Census Divisions.

	New England	**Middle Atlantic**	**South Atlantic**
Top three commercial activities, in terms of floor space	office, mercantile, education	office, warehouse and storage, mercantile	office, mercantile, warehouse and storage
Year of Construction			
Buildings built before 1960…….	41.8%	50.5%	28.3%
Buildings built after 1980………	16.3%	28.2%	44.8%
Building Energy Sources (%)			
Electricity………………………	91.3%	93.7%	95.1%
Natural Gas……………………..	21.6%	55.5%	30.9%
Fuel Oil…………………………	43.3%	26.7%	13.1%
Share of energy consumption			
Space Heating…………………..	43%	35%	21.2%
Cooling…………………………	3.6%	5%	10.8%
Lighting………………………....	18.2%	21.2%	27.3%
Percent of floorspace cooled			
50% or less……………………..	65.4%	63.3%	32.5%
100%…………………………...	19.7%	26.3%	48.7%
Building shell energy conservation features			
Multi-paned windows…………..	51.4%	49%	44.2%
Tinted or shading glass…………	14.4%	20.2%	26%

Source: Commercial Building Energy Consumption Survey, (EIA 2001c, 1997).

The commercial building stocks in New England and Middle Atlantic are considerably older with 42% and 51%, respectively, being built prior to 1960. In contrast, only 28% of commercial buildings in the South Atlantic were constructed prior to 1960 while nearly 45% have been constructed since 1980.

Energy sources used by the commercial sector vary by census division. Electricity is near universally used as an energy source in all three census divisions. Within the three eastern census divisions, commercial enterprises in the Middle Atlantic most commonly consume natural gas (56%) and New England has the largest share of commercial consumers (43%) using fuel oil.

Commercial energy use for space heating is significantly higher in New England (43%) than Middle Atlantic (35%) and the South Atlantic (21%) due to its cooler climate and larger share of commercial floor space devoted to activities requiring heating services such as education and office. Conversely, energy use for space cooling is highest at 11% in the South Atlantic and descends with increases in latitude to 5% in the Middle Atlantic and 4% in New England. Correspondingly, the share of floor-space cooled decreases with increases in latitude.

Building shell energy conservation measures are representative of adaptation to regional climatic conditions. Multi-paned windows are more common in the cooler New England and Middle Atlantic regions to reduce drafts and increase thermal efficiency. Tinted or shading glass, which is used to reduce solar heat gain, is found in 26% of commercial buildings in the South Atlantic as compared to 20% in the Middle Atlantic and 14% in New England.

5.3 Historic Energy Demand Profiles

Energy end-use systems – whether they are households, cities, states, census regions, or nations – exhibit unique energy demand responses to climate. These unique characteristics include differences in energy demand sensitivities to changes in temperature and balance point temperatures, which themselves both arise, at least in part, as a consequence of adaptation to the local climatic conditions.

This section utilizes scatter plots of historic monthly energy demands and population-weighted 30-year average monthly temperatures to visually examine the degree of variation in energy demand responses to climatic conditions between the census divisions and individual states. Visual inspection can reveal (1) the balance point temperature of a system as that temperature at the bottom of the V-shaped energy use-temperature relation and (2) differences in energy demand sensitivities to 'hot' and 'cold' temperatures by examining the slope of the energy demand-temperature relation. Additionally, since the scatter plots assist in communicating the unique energy demand characteristics of each census division and state as well as differences between them, the scatter plots act as a validity benchmark for the statistical results detailed in chapter 6.

The relationships between residential electricity sales per capita and mean monthly population-weighted temperature by census division and individual states (grouped by census division) are shown in Figures 12-15, respectively. All census divisions and states exhibit a V-shaped electricity sales-temperature relationship. In both the New England and Middle Atlantic census divisions, the balance point temperature of the residential sector appears to be slightly below 60°F. The balance point temperature in the South Atlantic, on the other hand, appears to be above 60°F. Balance points for individual states are observed to be at similar temperatures to their respective census divisions since census division figures are, in fact, the population-weighted aggregates of the state-level data. The lower balance point temperatures observed in more northern states relative to more southern states is likely a consequence of adaptation by energy users to the local climate characteristics. For example, residential housing units in northern states are required to have greater amounts of insulation to protect from the cold weather which, in turn, would decrease the temperature point at which heating services would be required.

Not only are regional variations in balance point temperature observable, but so too are differences in energy demand sensitivities to ‘hot’ and ‘cold’ temperatures. The slope of both arms of the V-shaped electricity demand-temperature relationship graphically represents energy demand sensitivities to changes in temperature. The portion of the electricity sales-temperature relation to the right of the balance point is the energy demand sensitivity to ‘hot’ temperatures, whereas the portion of the electricity sales-temperature relation to the left of the balance point is the energy demand sensitivity to ‘cold’ temperatures. For instance, with respect to the South Atlantic’s electricity sensitivity to hot temperatures we observe per capita electricity demand increasing relatively rapidly from approximately 300 kWh per person at 65°F to near 600 kWh per person at 80°F, a 100% increase. In contrast, New England’s electricity sensitivity to hot temperature only appears to increase from 200 kWh per person at 55°F to 250 kWh per person at 70°F, a 25% increase.

Figures 16-19 are scatter plots of commercial electricity sales per employee and mean monthly population-weighted temperature by census division and individual states (grouped by census division). Commercial buildings typically have lower balance point temperatures than residential dwellings due to higher internal heat gains from office machinery, lighting and occupants. In general, the figures indicate that the commercial sectors of census divisions and states have lower balance point temperatures relative to that observed for the residential sector. The figures also suggest that non-temperature sensitive electricity demand has been increasing over the period of analysis because the V-shaped electricity-temperature relation shows a vertical movement. Moreover, commercial electricity sensitivities to hot and cold temperatures – as indicated by the steepness of each arm of the V-shape energy demand-temperature relation – are lower than in the residential sector.

The relationships between residential natural consumption and mean monthly population-weighted temperature by census division and in individual states (grouped by census division) are shown in Figures 20-23, respectively. For all census divisions and states the relationship is a downward sloping function because natural gas is predominantly used to provide heating services. Hence, heating energy demand requirements decrease with warmer temperatures. Consequently, for energy sources predominantly used to provide heating services (i.e. natural gas and heating oil) the balance point is not the temperature at the bottom of the V-shaped relation as it is with electricity, but is instead that temperature above which energy use no longer decreases. We can see in Figure 23, for example, that natural gas sales in Virginia cease declining with increases in temperature above roughly 70˚F, which indicates a balance point temperature of approximately 70˚F. The census division and state figures suggest balance points between 70˚F and 75˚F. Finally, the figures of the natural gas sales-temperature relation indicate similarly high demand sensitivity in each region.

Figures 24-27 contain the scatter plots of the commercial natural gas sales and population-weighted temperature by census division and in individual states (grouped by census division). All census divisions and states show a inverse relation between temperature and commercial natural gas sales and similar balance points between 65˚F and 70˚F, with the exception of Florida where the balance point appears to be in the high 70s.

The relationships between heating oil sales and mean monthly population-weighted temperature by census division and in individual states (grouped by census division) are shown in Figures 28-31, respectively. The significantly larger values for heating oil sales per capita on the vertical axis of the New England and Middle Atlantic divisions attest to the fact that the vast majority of heating oil sales in the U.S. are to these areas (see Figure 28). Moreover, the correlation between heating oil sales and temperature appears to be much stronger in the northern census divisions compared to the South Atlantic. In fact in a few states, such as West Virginia and Georgia, there appears to be little correlation between heating oil sales and temperature (see Figure 31).

Figure 12. Census Divisions' Monthly Residential Electricity Use and Population-weighted Temperature, 1977-2001.

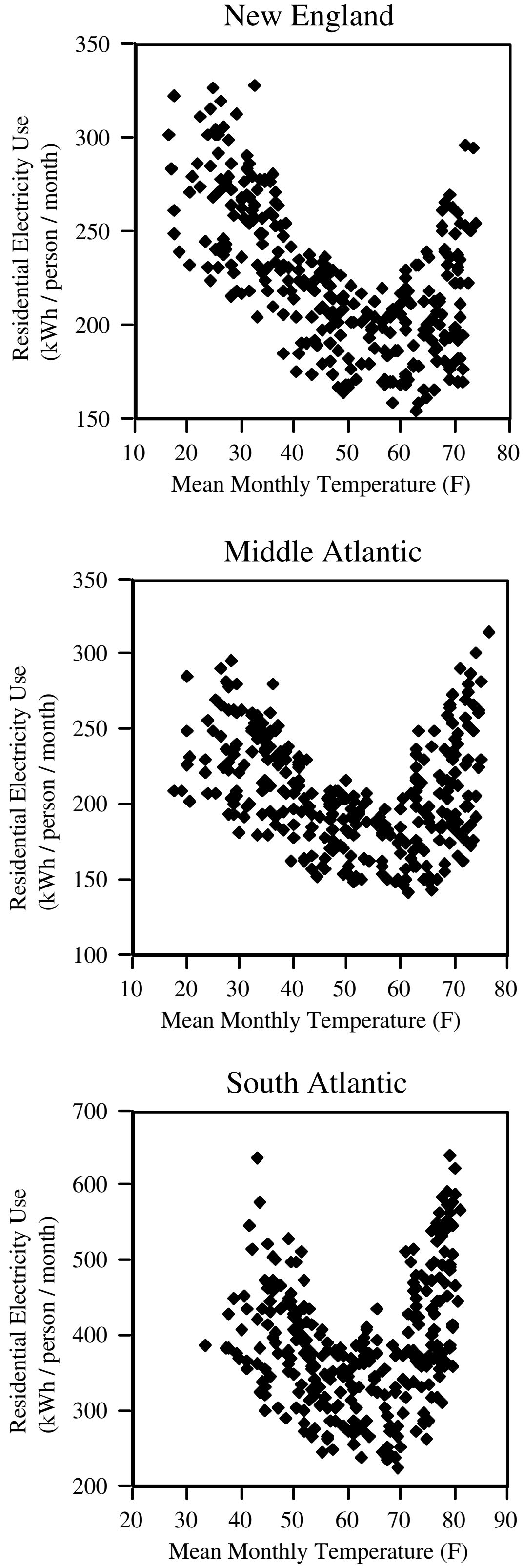


Figure 13. New England States' Monthly Residential Electricity Use and Population-weighted Temperature, 1977-2001.

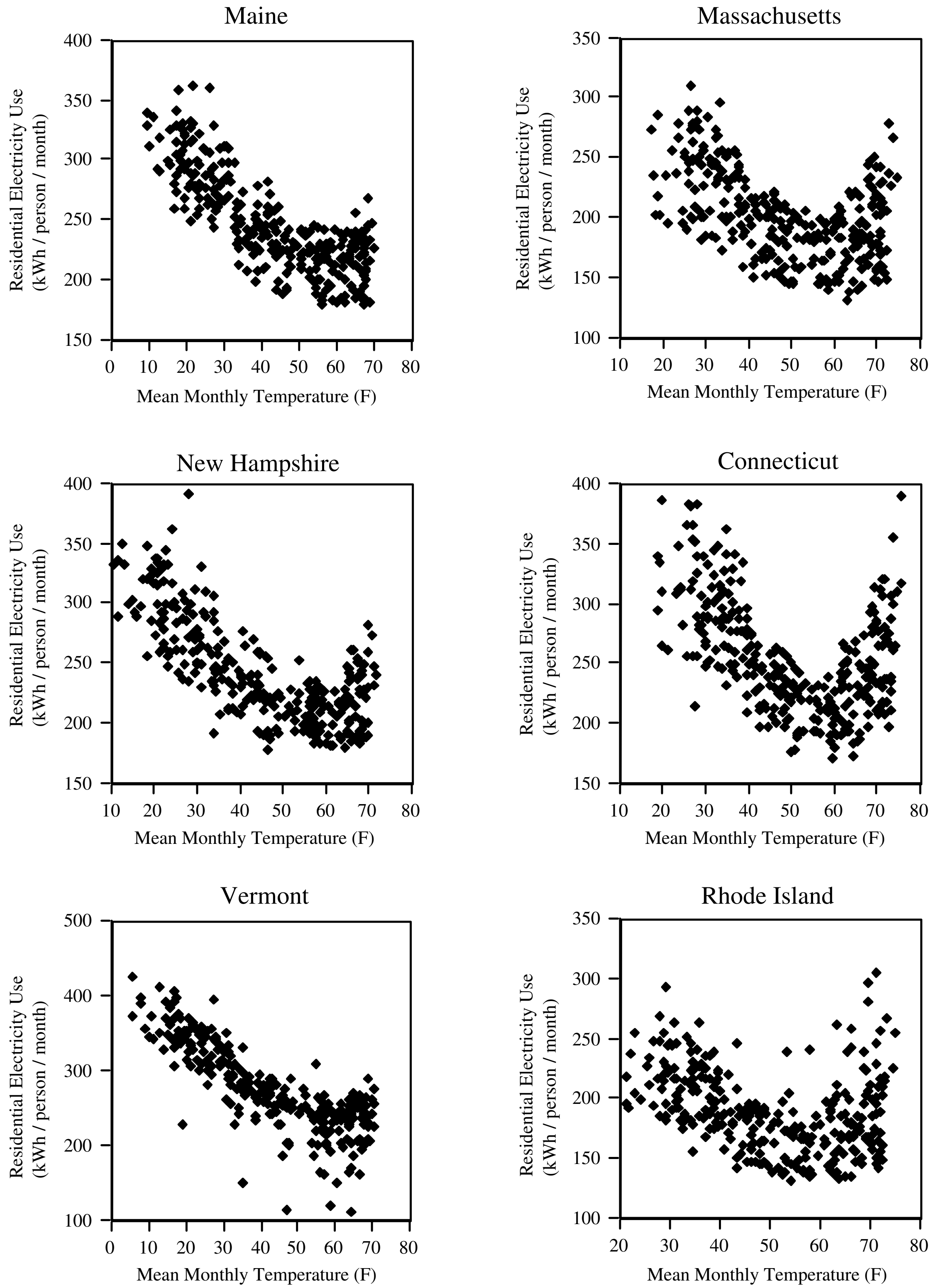


Figure 14. Middle Atlantic States' Monthly Residential Electricity Use and Population-weighted Temperature, 1977-2001.

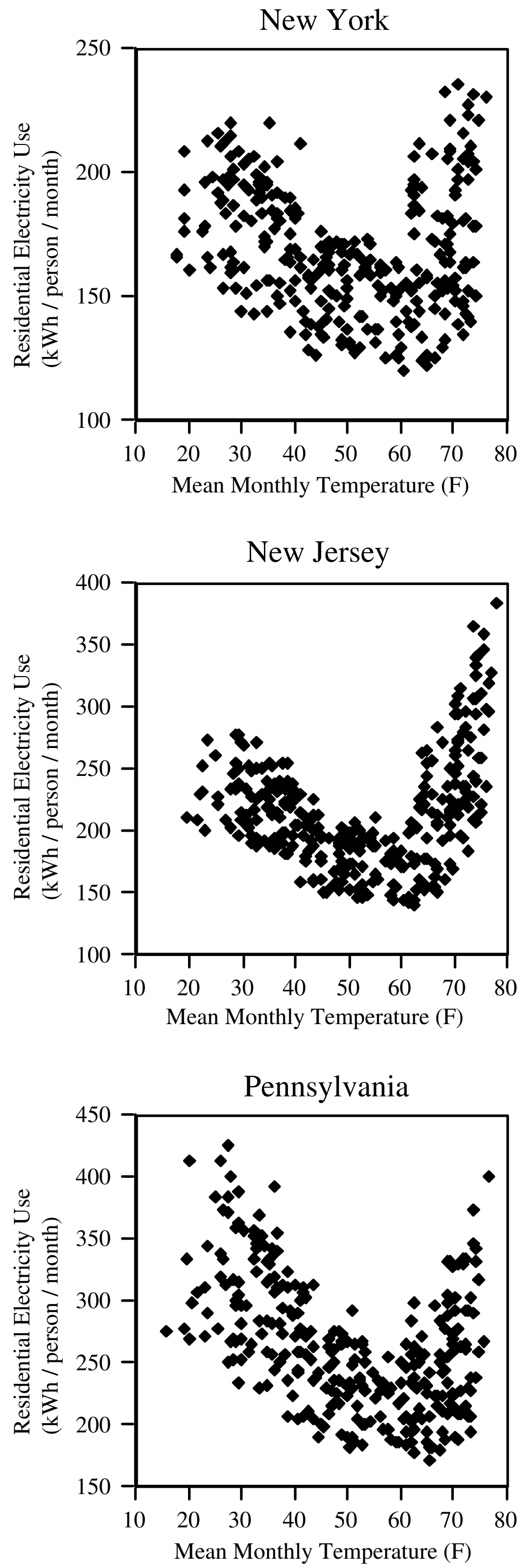


Figure 15. South Atlantic States' Monthly Residential Electricity Use and Population-weighted Temperature, 1977-2001.

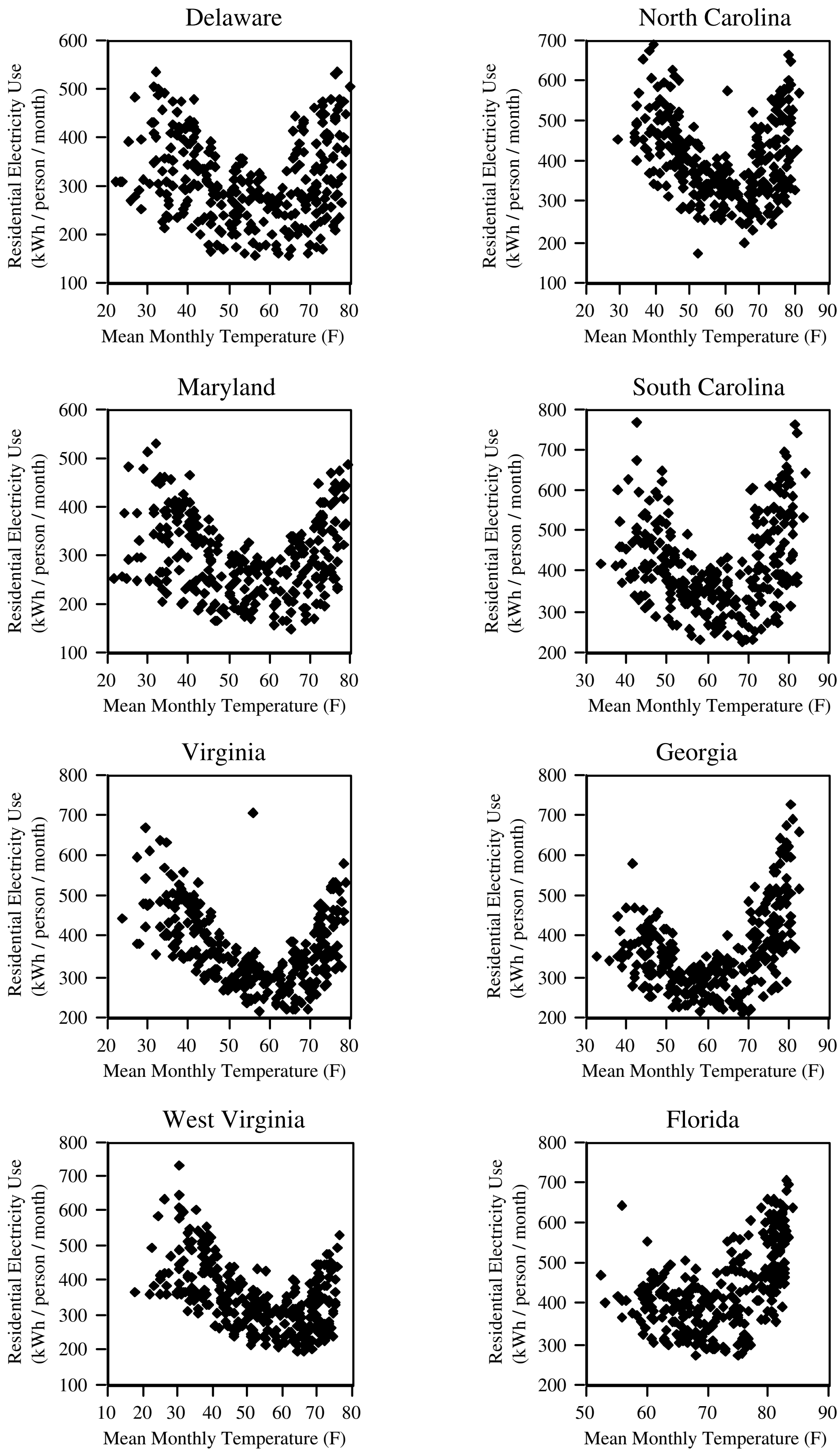


Figure 16. Census Divisions' Monthly Commercial Electricity Use and Population-weighted Temperature, 1977-2001.

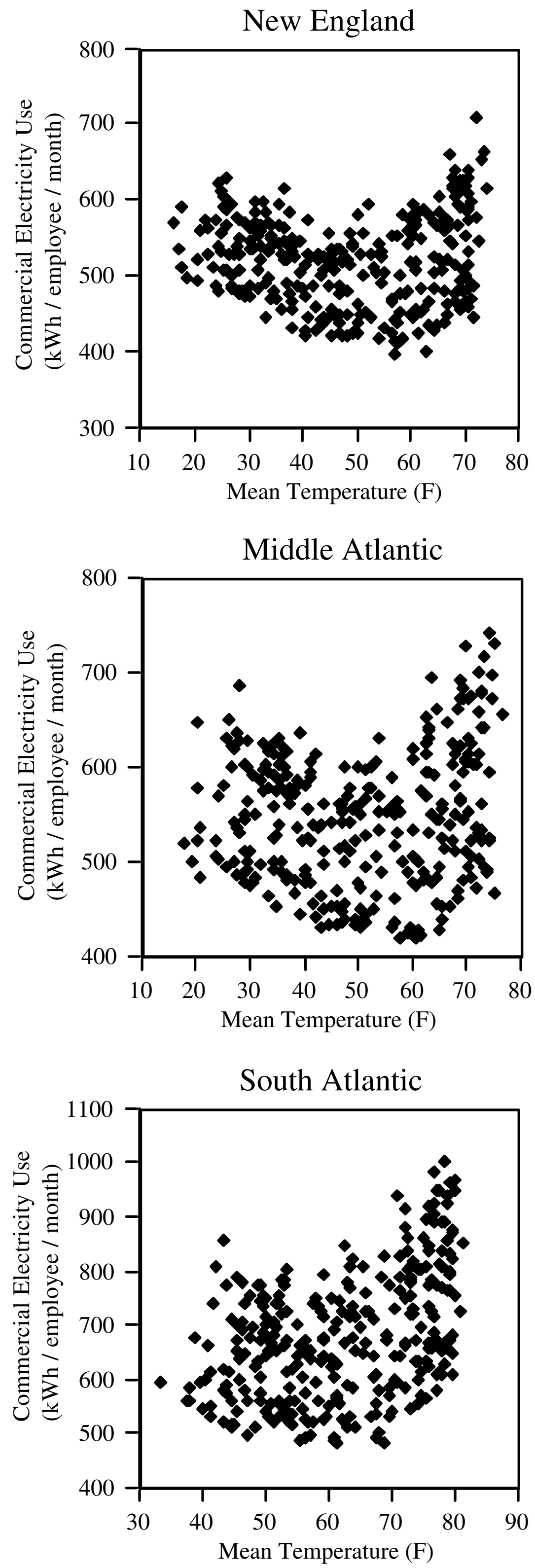


Figure 17. New England States' Monthly Commercial Electricity Use and Population-weighted Temperature, 1977-2001.

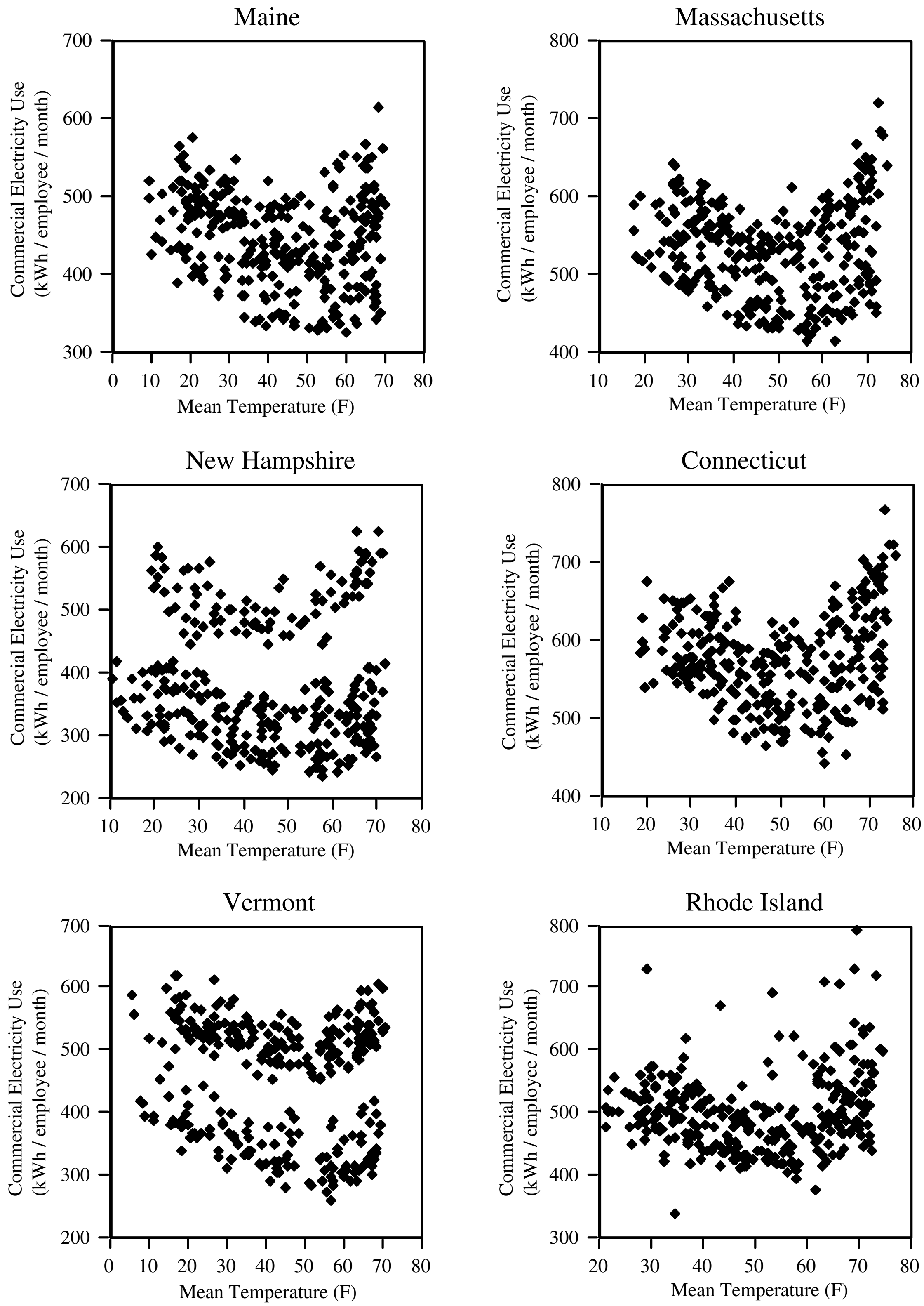


Figure 18. Middle Atlantic States' Monthly Commercial Electricity Use and Population-weighted Temperature, 1977-2001.

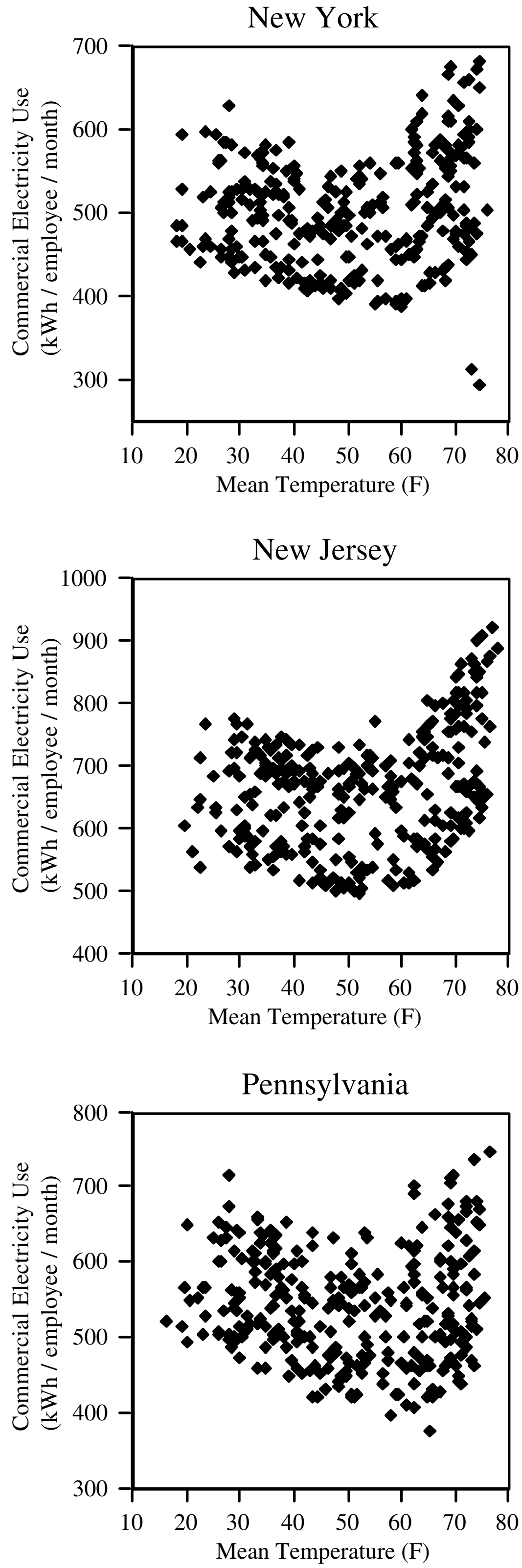


Figure 19. South Atlantic States' Monthly Commercial Electricity Use and Population-weighted Temperature, 1977-2001.

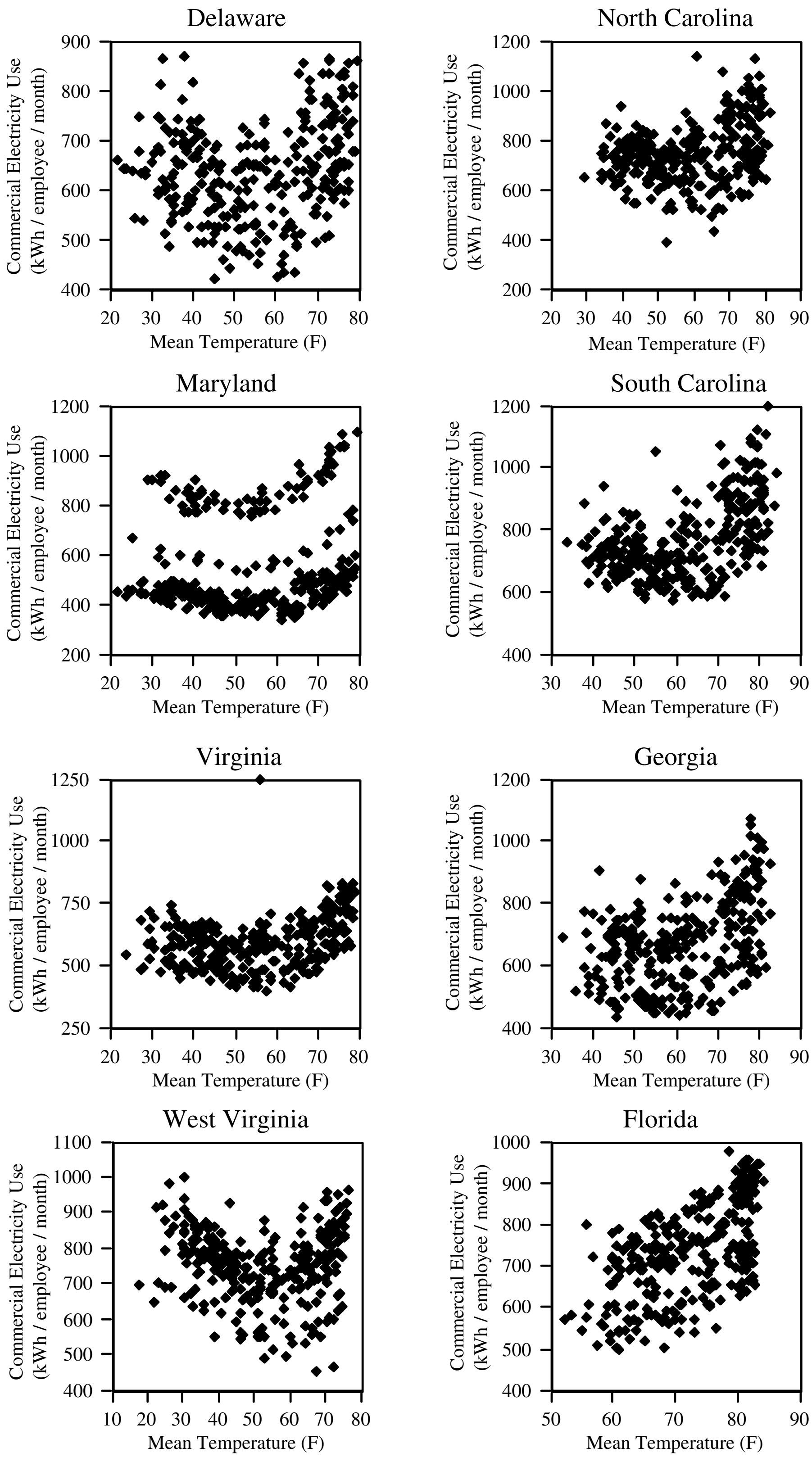


Figure 20. Census Divisions' Monthly Residential Natural Gas Sales and Population-weighted Temperature, 1984-2001.

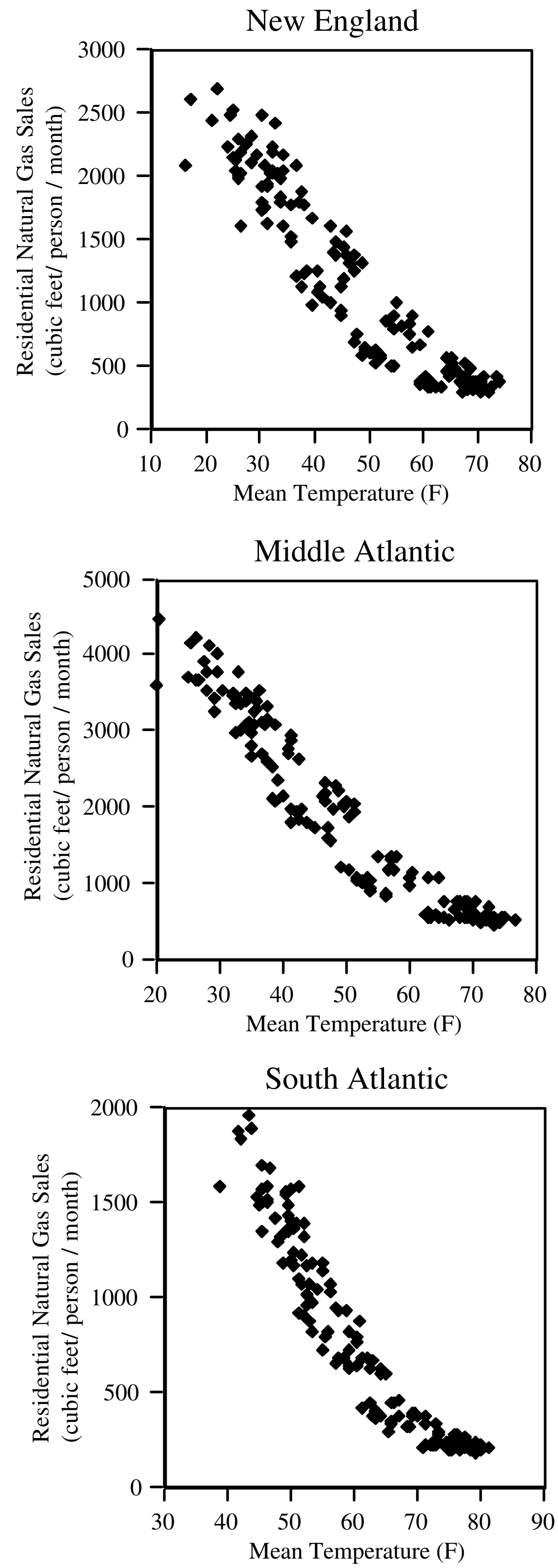


Figure 21. New England States' Monthly Residential Natural Gas Sales and Population-weighted Temperature, 1984-2001.

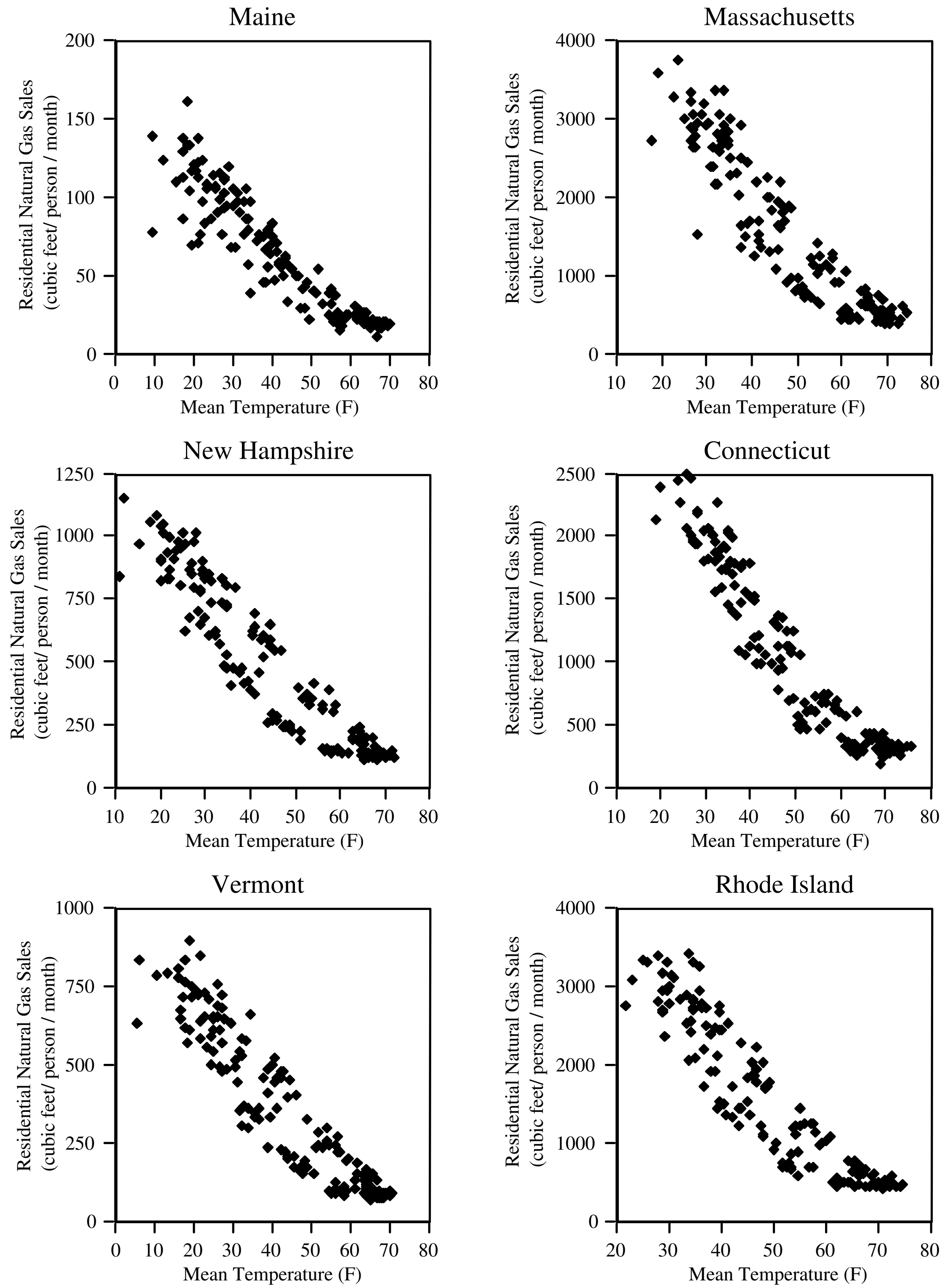
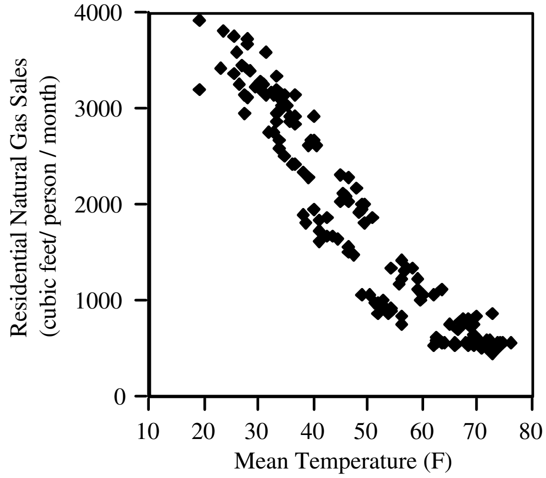
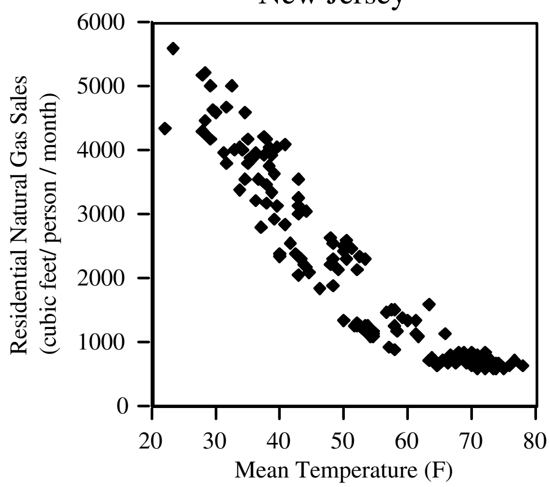


Figure 22. Middle Atlantic States' Monthly Residential Natural Gas Sales and Population-weighted Temperature, 1984-2001.

New York



New Jersey



Pennsylvania

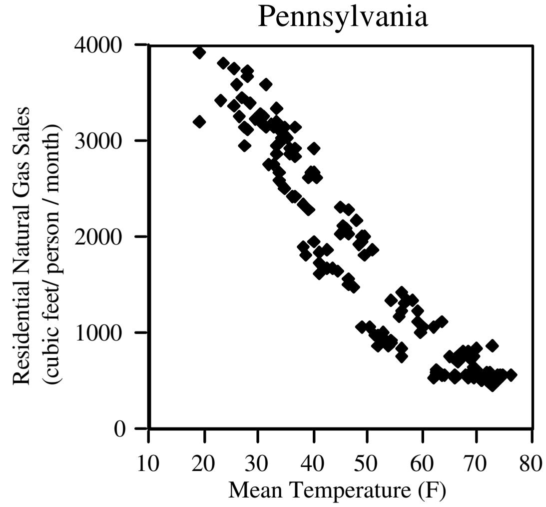


Figure 23. South Atlantic States' Monthly Residential Natural Gas Sales and Population-weighted Temperature, 1984-2001.

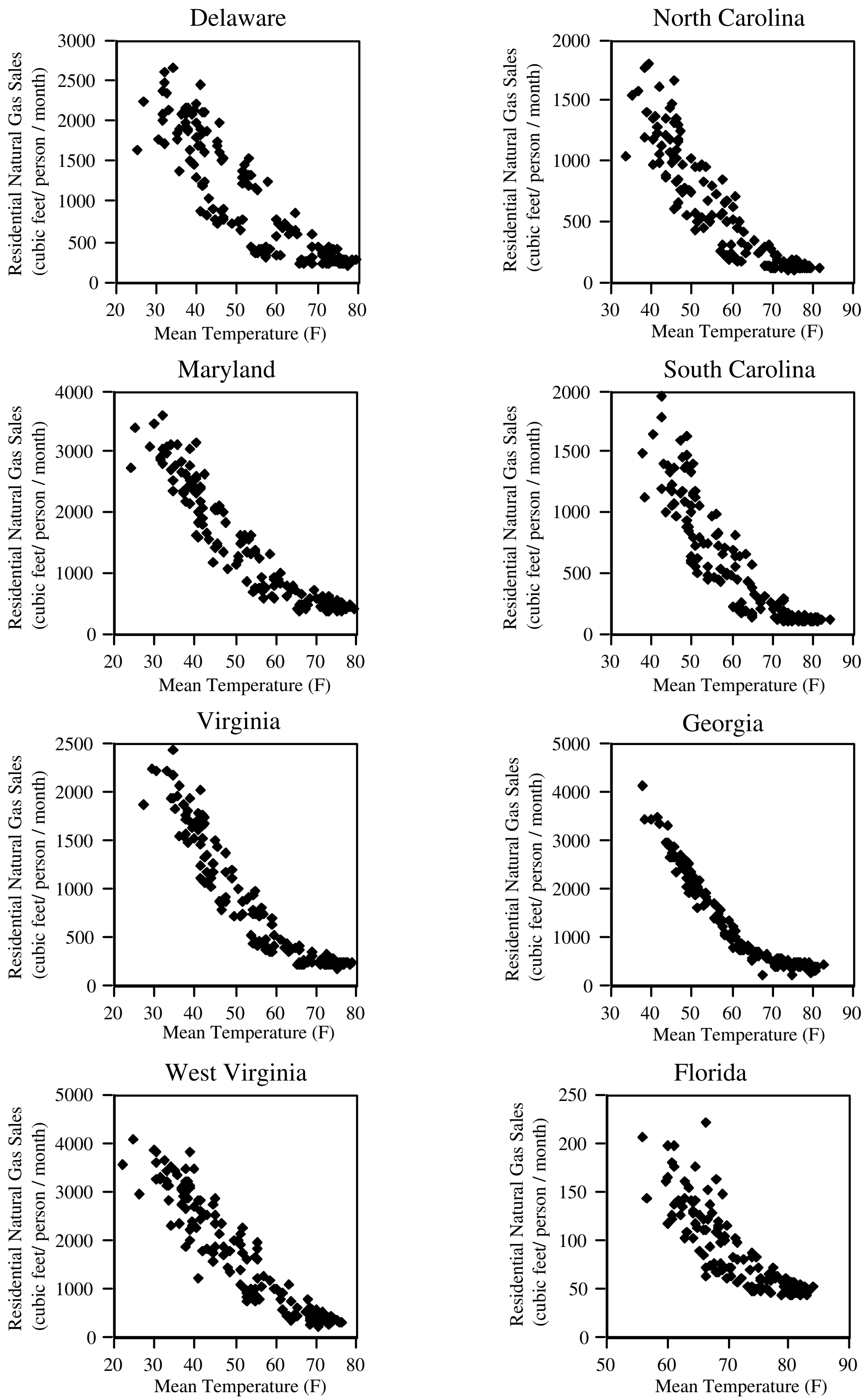


Figure 24. Census Divisions' Monthly Commercial Natural Gas Sales and Population-weighted Temperature, 1984-2001.

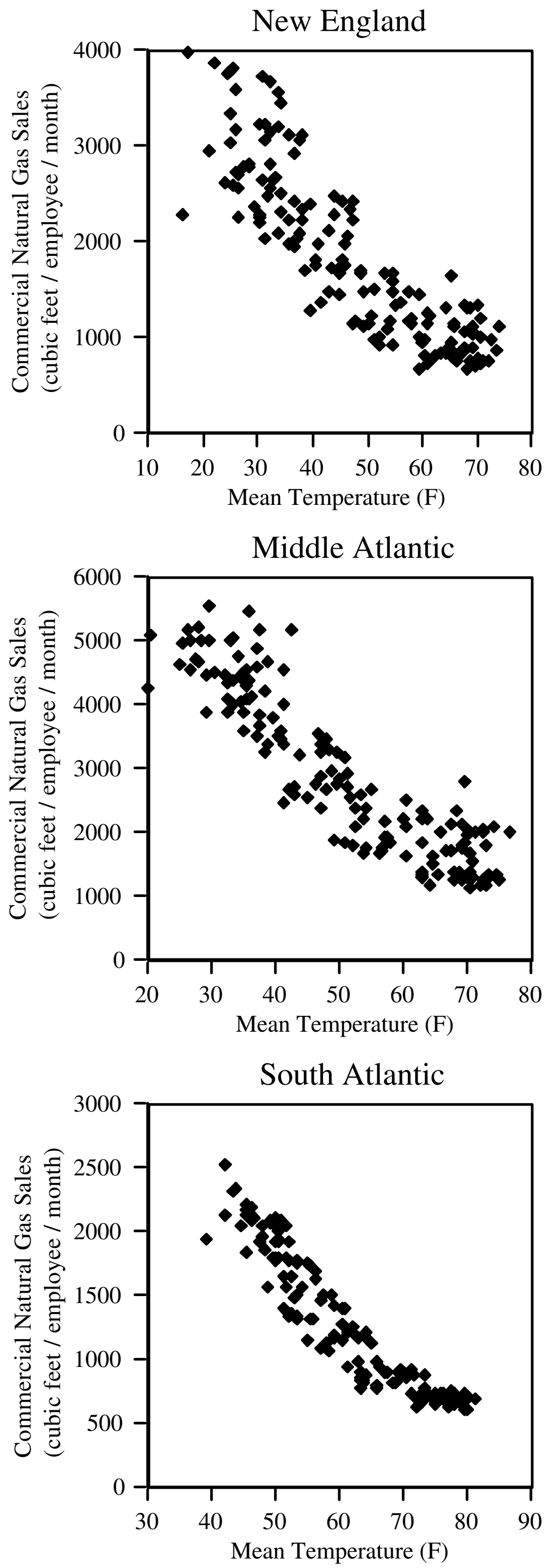


Figure 25. New England States' Monthly Commercial Natural Gas Sales and Population-weighted Temperature, 1984-2001.

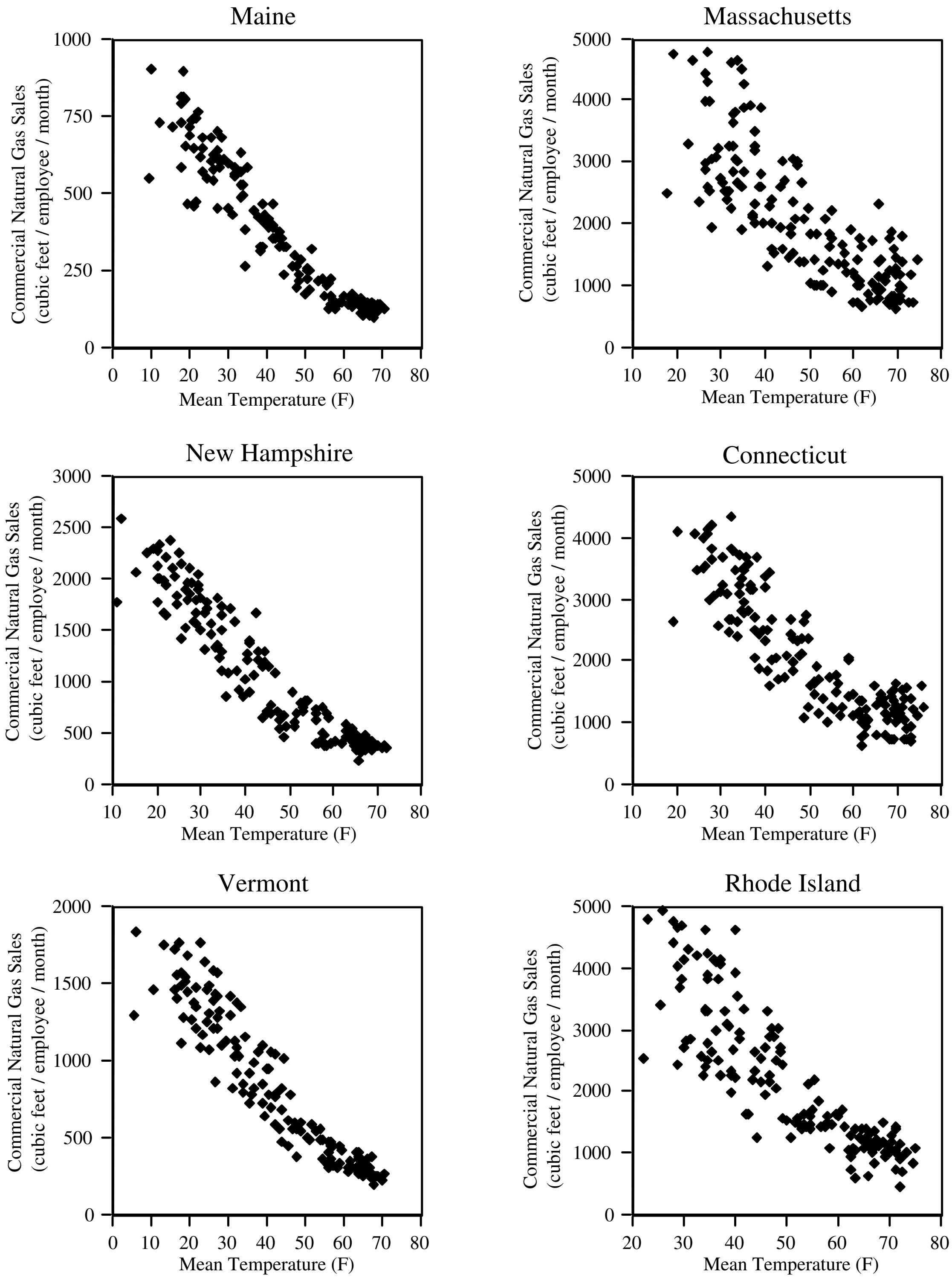


Figure 26. Middle Atlantic States' Monthly Commercial Natural Gas Sales and Population-weighted Temperature, 1984-2001.

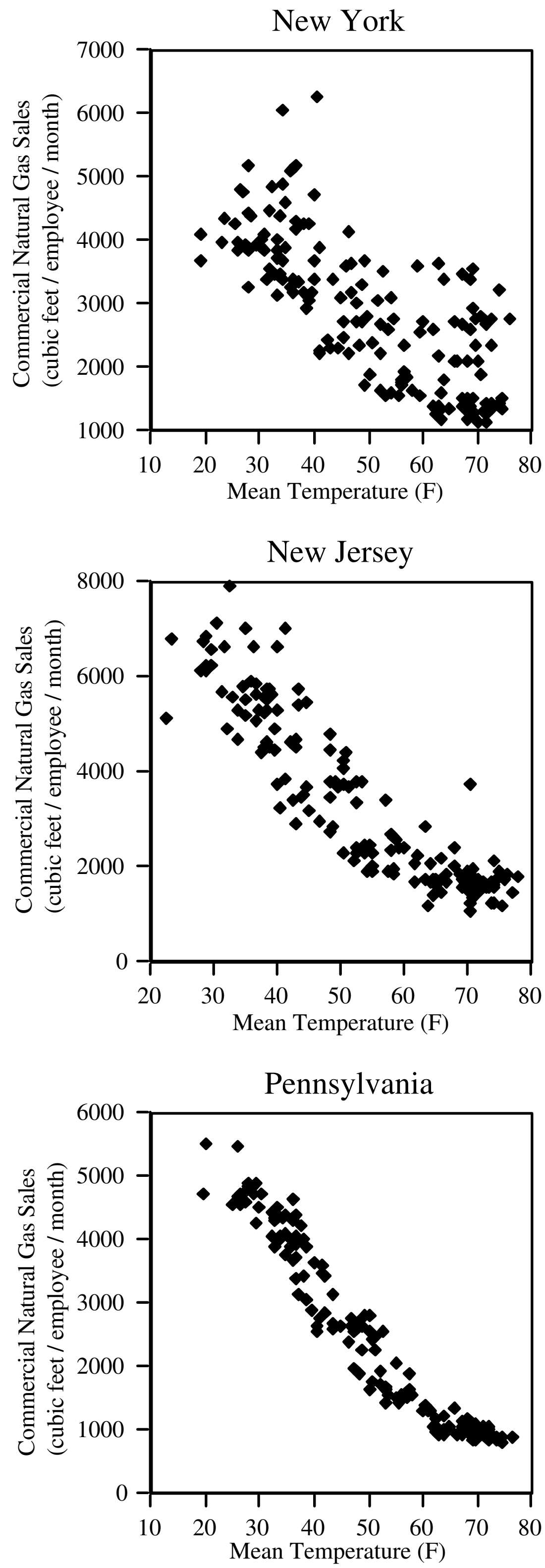


Figure 27. South Atlantic States' Monthly Commercial Natural Gas Sales and Population-weighted Temperature, 1984-2001.

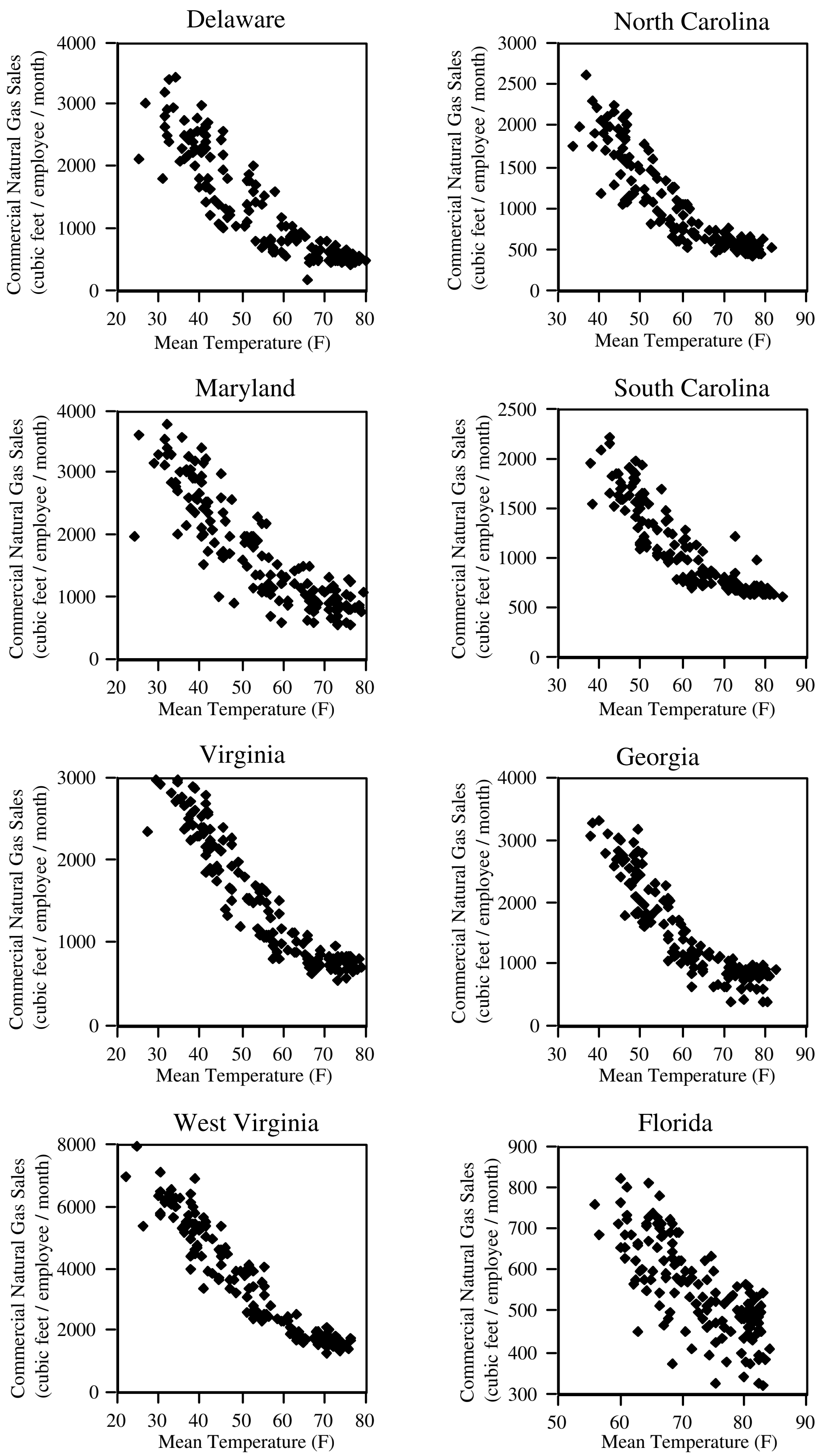


Figure 28. Census Divisions' Monthly Residential Heating Oil Sales and Population-weighted Temperature, 1983-2001.

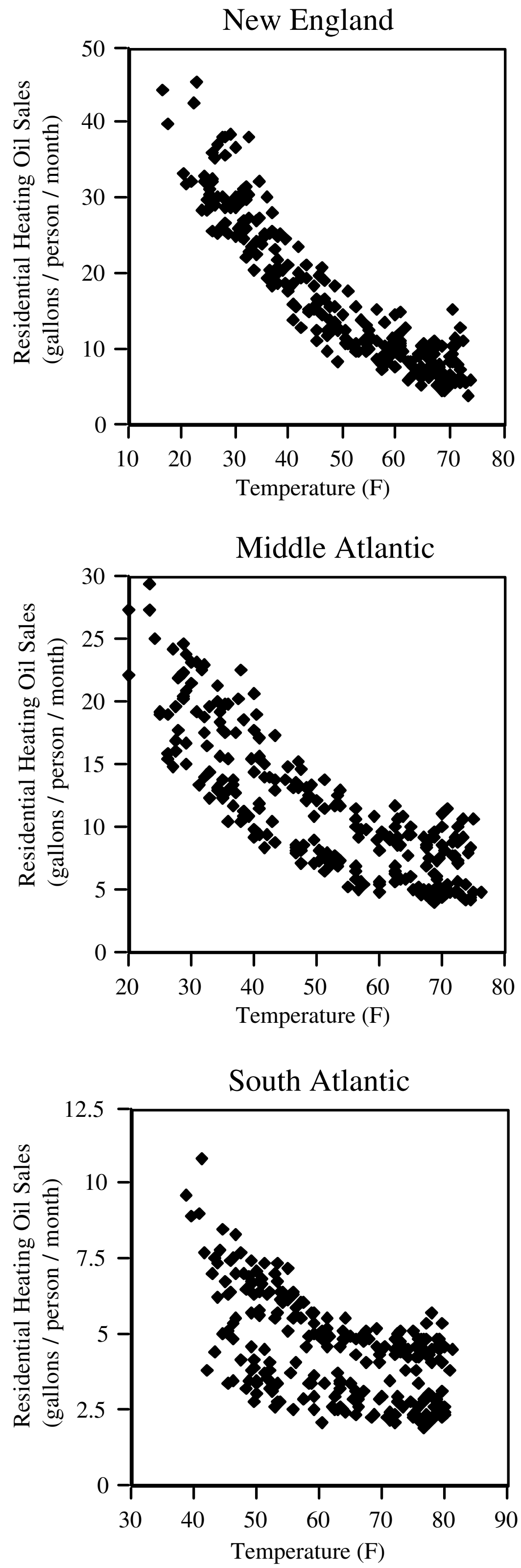


Figure 29. New England States' Monthly Residential Heating Oil Sales and Population-weighted Temperature, 1983-2001.

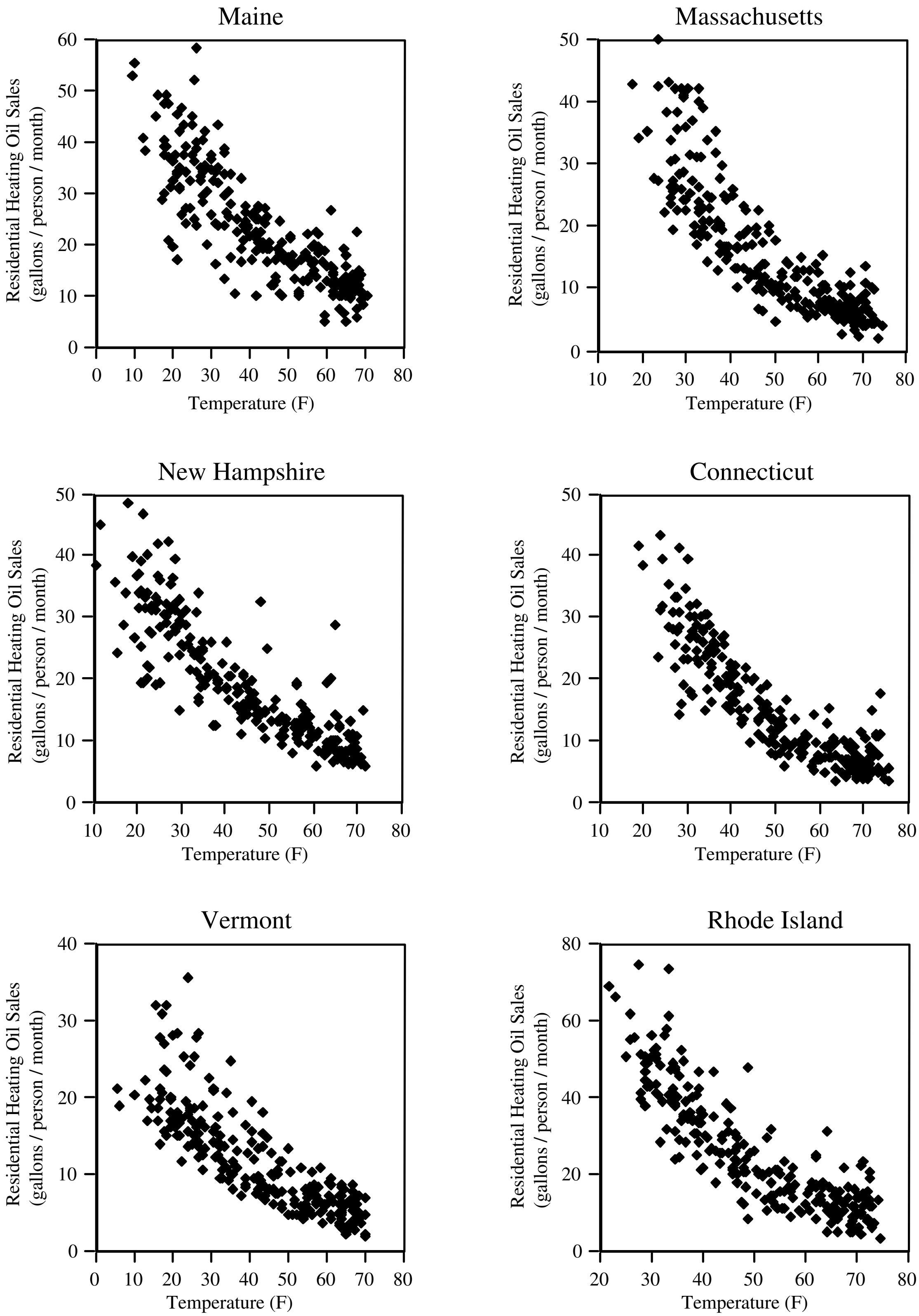


Figure 30. Middle Atlantic States' Monthly Residential Heating Oil Sales and Population-weighted Temperature, 1983-2001.

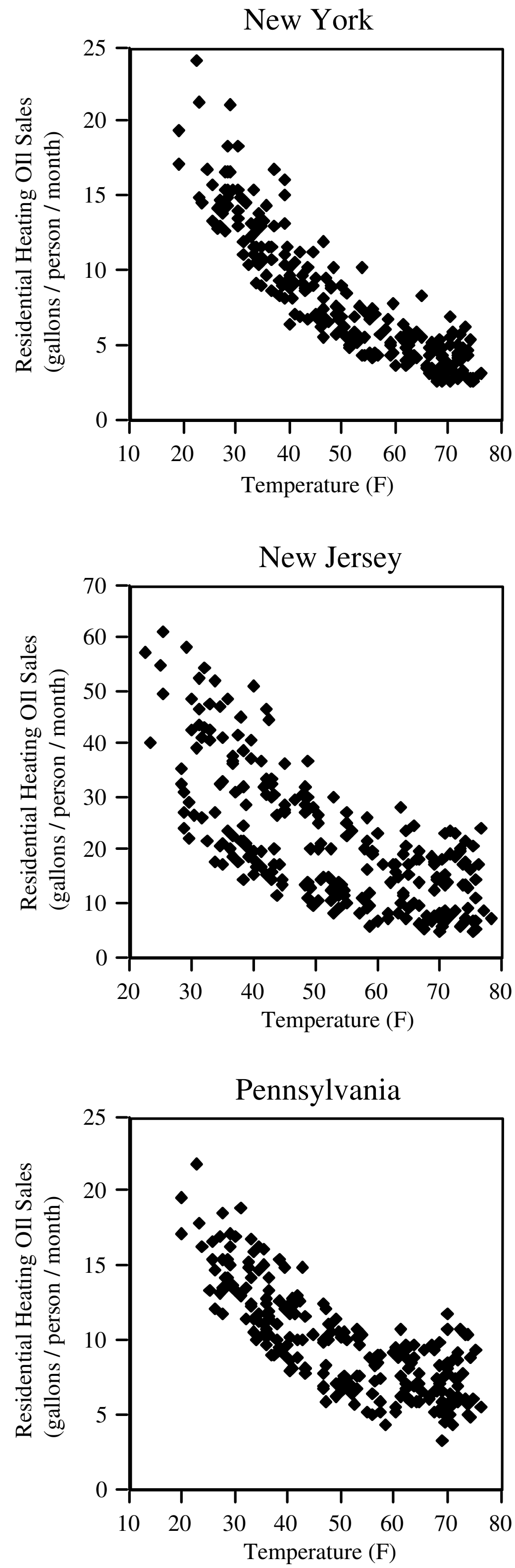
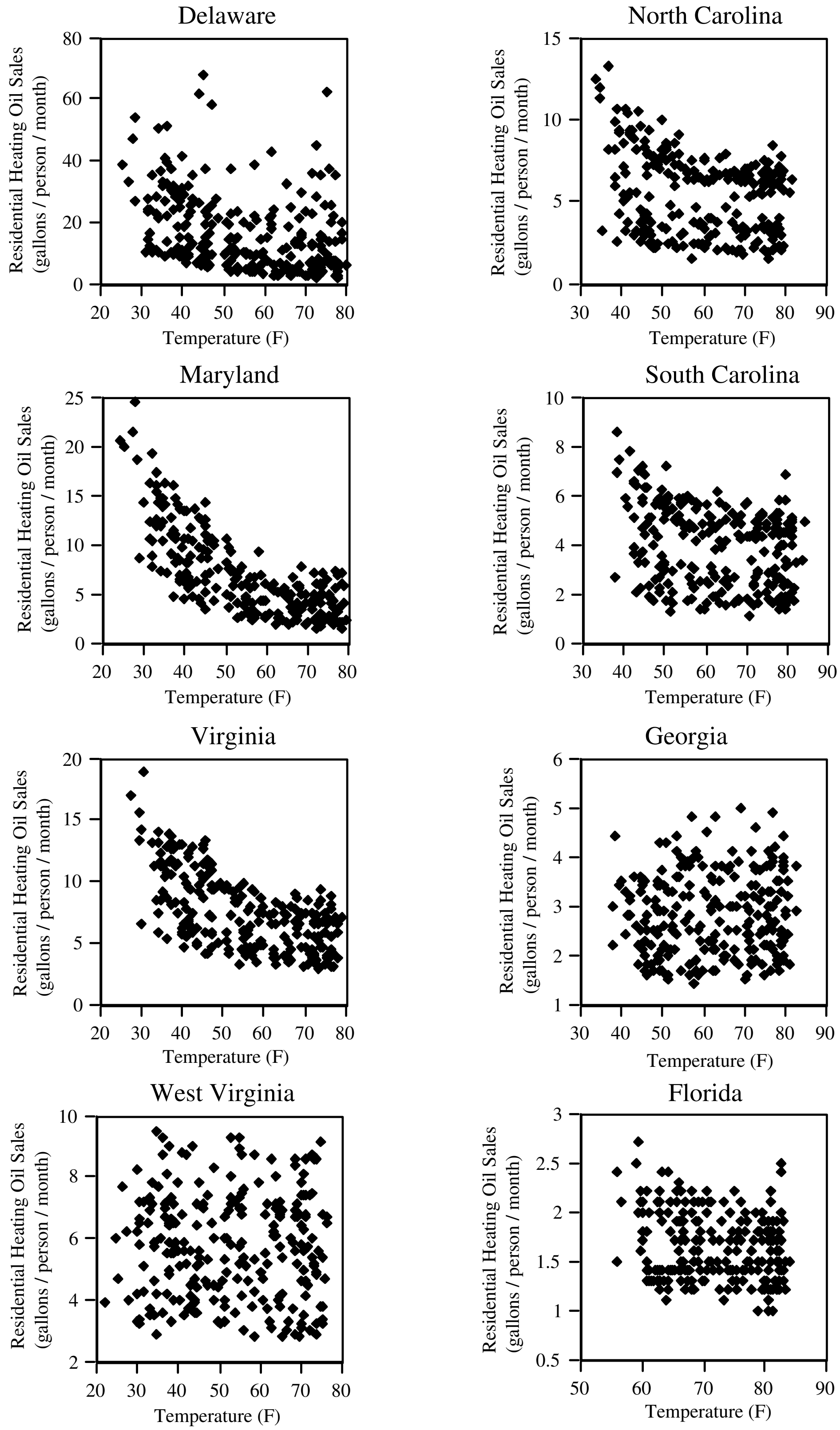


Figure 31. South Atlantic States' Monthly Residential Heating Oil Sales and Population-weighted Temperature, 1983-2001.



6. Temporal and Geographic Analyses Findings

To make projections of energy demand responses to climate and climate change scenarios this study utilizes a temporal analysis and a geographic analysis. The temporal analysis quantifies the historic sensitivity of states' energy demands to climatic variability whereas the geographic analysis provides estimates of the adaptive capacity of energy users to climatic change.

Sections 6.1 and 6.2 review the results of the temporal analysis, which employed econometric models to estimate historic relations between energy demand and degree-days while controlling for other relevant factors[2]. Section 6.1 details the regression models specified with static energy demand sensitivities, which quantify the *average* energy demand sensitivity to changes in degree-days over the period of analysis. Statistical models are only presented for degree-days generated from the balance point temperature that produced the highest R-square for the respective state or census division.

In section 6.2, a dynamic energy demand sensitivity component is introduced into the statistical models developed in section 6.1. The dynamic degree-day sensitivity variables assess if and to what extent energy demand sensitivities to degree-days have changed over the period of analysis. The dynamic variables were introduced because, as was hypothesized, energy demand sensitivity to degree-days could have changed with changes in the percent of the population using the energy for space-conditioning, changes in the efficiency of space-conditioning technologies, or changes in demand patterns for space-conditioning technologies.

[2] The reader is encouraged to validate the statistical findings detailed in the subsequent sections with the scatter plots of the historic relations between energy demand and population-weighted temperature in states and census divisions presented in section 5.3.

The geographic analysis of section 6.3 compares the state-level energy demand sensitivity findings of section 6.1 to discern adaptation by energy user to current climatic conditions, and from these findings develop metrics to assess the potential for adaptation to climate change.

6.1 Temporal Analysis Results with Static Sensitivities

6.1.1 Residential Electricity Results

Residential electricity results for census divisions are reported in Table 9. The outdoor average temperature that produces the desired indoor comfort level is lower in New England and the Middle Atlantic than in the South Atlantic. A balance point temperature of 56˚F is observed in both New England and the Middle Atlantic, whereas a balance point temperature of 63˚F is observed in the South Atlantic. The balance point temperature findings support the hypothesis that in warmer climates heating services are demanded at higher temperatures than in cooler climates and, conversely, that cooling services are demanded at lower temperatures in cooler climates than in warmer climates.

Per capita electricity demand responses to deviations in degree-days are markedly different in each census division. With respect to electricity demand sensitivity to cold, a 100 unit increase in heating degree-days is associated with a 4.4% increase in per capita electricity demand in New England, a 3.6% increase in the Middle Atlantic, and a 7.6% increase in the South Atlantic. The large sensitivity of electricity demand in the South Atlantic to heating degree-days is not surprising since electricity is the predominant heating energy type. Smaller per capita sensitivities would be expected, and are in fact observed, in New England and Middle Atlantic because considerably fewer people use electricity as the main heating energy source. Additionally, residential housing units in the South Atlantic are more likely to have less insulation and, thus, a higher sensitivity to cold.

Each census division's electricity demand is more sensitive to hot than to cold temperatures. A 100 unit increase in cooling degree-days is associated with a 5.6% increase in per capita electricity demand in New England, a 8.3% increase in the Middle Atlantic, and a 13.9% increase in the South Atlantic. The observation of higher sensitivities of electricity demand to hot temperatures in warmer climates is likely a result of the significantly greater prevalence of air-conditioning in those regions (refer to Table 7 in section 5.1).

The hours of daylight variable indicates that more hours of daylight are associated with lower electricity demand per capita per month. Electricity demand decreases by 0.7%, 1.8%, and 1.6% for each additional hour of daylight in the New England, Middle Atlantic, and South Atlantic census divisions, respectively. The price of electricity is also inversely related to per capita electricity demand with higher monthly electricity associated with lower electricity demand per capita. A 10% increase in the price of electricity is associated with a 4.5% decrease in electricity demand in New England, a 8.5% decrease in the Middle Atlantic, and a 11.0% decrease in the South Atlantic. Finally, the results suggest that non-temperature sensitive electricity demand has increased at an average annual rate of between 0.5% and 1.2% per year, which is likely attributable to increasing proliferation of electronic devices (Sanchez et al., 1998).

The individual state responses are similar to the results at the census divisional level (see Tables 10-12). The results for states suggest balance point temperatures ranging from 53˚F to 57˚F in New England states, 53˚F to 60˚F in Middle Atlantic states, and 56˚F to 68˚F in South Atlantic states. Electricity demand sensitivities to heating degree-days ranged from 3.3% to 5.3% in New England states, 2.3% to 5.0% in Middle Atlantic states, and 5.6% to 9.5% in South Atlantic states. Electricity demand sensitivities to cooling degree-days ranged from 1.4% to 8.0% in New England states, 5.6% to 12.4% in Middle Atlantic states, and 8.2% to 16.1% in South Atlantic states.

Table 9. Census Divisions' Residential Electricity Regression Results with Static Sensitivities.

	New England Electricity per Capita (log)	Middle Atlantic Electricity per Capita (log)	South Atlantic Electricity per Capita (log)
Balance Point Temperature (F)	56	56	63
Constant	6.276432***	7.201321***	7.815236***
Annual Trend	0.0068972***	0.006454***	0.0120211***
Heating Degree-days	0.0004366***	0.0003555***	0.0007554***
Cooling Degree-days	0.0005552***	0.0008266***	0.0013929***
Hours of Daylight	-0.0069813*	-0.0175562***	-0.015787**
Electricity Price (log)	-0.4531042***	-0.8525552***	-1.096437***
R-squared	0.8264	0.7915	0.8491
DW (transformed)	1.856162	1.734354	1.788051

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 10. New England States' Residential Electricity Regression Results with Static Sensitivities.

	Maine Electricity per Capita (log)	New Hampshire Electricity per Capita (log)	Vermont Electricity per Capita (log)	Massachusetts Electricity per Capita (log)	Connecticut Electricity per Capita (log)	Rhode Island Electricity per Capita (log)
Balance Point Temperature (F)	53	55	55	55	57	55
Constant	5.668716***	5.896099***	5.474535***	5.783445***	5.913428***	5.860017***
Annual Trend	0.0001216	0.0006514	-0.0014964	0.0075194***	0.0087795***	0.0136333***
Heating Degree-days	0.0003319***	0.0004237***	0.0003819***	0.0004314***	0.0005293***	0.0003782***
Cooling Degree-days	0.0001395***	0.0004025***	0.0003353***	0.00049***	0.0007959***	0.0005805***
Hours of Daylight	0.0056639	0.0055472	-0.0055622	-0.0096199	-0.0110193**	-0.0148551*
Electricity Price (log)	-0.1658468	-0.2984352***	0.0152878	-0.2470014***	-0.232944*	-0.2902737***
R-squared	0.7064	0.7561	0.8645	0.7699	0.8486	0.5534
DW (transformed)	2.043373	1.976249	1.853010	1.858905	1.943934	1.999280

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 11. Middle Atlantic States' Residential Electricity Regression Results with Static Sensitivities.

	New York Electricity per Capita (log)	New Jersey Electricity per Capita (log)	Pennsylvania Electricity per Capita (log)
Balance Point Temperature (F)	53	57	60
Constant	7.068403***	5.327644***	6.250813***
Annual Trend	0.009669***	0.0100867***	0.0090304***
Heating Degree-days	0.0002364***	0.0004106***	0.0005039***
Cooling Degree-days	0.0005621***	0.0012366***	0.0009882***
Hours of Daylight	-0.0267224***	-0.0231395***	0.0006589
Electricity Price (log)	-0.7614857***	0.0125471	-0.4736089***
R-squared	0.6226	0.8659	0.8240
DW (transformed)	1.601865	1.845677	1.834642

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 12. South Atlantic States' Residential Electricity Regression Results with Static Sensitivities.

	Delaware Electricity per Capita (log)	Maryland Electricity per Capita (log)	Virginia Electricity per Capita (log)	West Virginia Electricity per Capita (log)	North Carolina Electricity per Capita (log)	South Carolina Electricity per Capita (log)	Georgia Electricity per Capita (log)	Florida Electricity per Capita (log)
Balance Point Temperature (F)	56	60	61	62	61	64	61	68
Constant	7.41769***	5.47307***	6.03568***	6.35353***	7.51931***	9.68721***	6.13558***	8.39285***
Annual Trend	0.012673***	0.013038***	0.010098***	0.017778***	0.00892**	0.014034***	0.016863***	0.013165***
Heating Degree-days	0.000616***	0.000749***	0.000954***	0.000754***	0.000823***	0.000703***	0.000788***	0.000562***
Cooling Degree-days	0.000824***	0.001164***	0.001374***	0.001097***	0.001094***	0.001098***	0.001606***	0.001241***
Hours of Daylight	-0.0131147	0.0021004	0.0074225	0.0076476	-0.0173216	-0.0185664	-0.02555***	-0.05051***
Electricity Price (log)	-0.87843***	-0.06987	-0.34092***	-0.56557***	-0.85645***	-2.03956***	-0.214824	-1.05111***
R-squared	0.5879	0.8495	0.9342	0.8887	0.7068	0.7320	0.9272	0.8746
DW (transformed)	1.796617	1.894963	1.862790	2.018937	1.804206	1.750137	1.959642	1.950915

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.1.2 Residential Natural Gas Results

Table 13 presents the residential natural gas regression results for the New England, Middle Atlantic, and South Atlantic census divisions. The observed balance point temperatures suggest that natural gas is consumed for space heating at higher temperatures in the South Atlantic than in either the Middle Atlantic or New England regions. Put another way, energy users in warmer climates perceive 'cold' at a higher temperature. The South Atlantic has a balance point temperature of 75˚F, while New England and the Middle Atlantic have balance point temperature of 69˚F and 70˚F, respectively.

The sensitivity of per capita natural gas demand to heating degree-days is the smallest in the Middle Atlantic where a 100 unit increase in heating degree-days is associated with a 10.3% increase in natural gas demand. New England and the South Atlantic have natural gas sensitivities of 18.6% and 20.5%, respectively. One possible explanation for the smaller sensitivity of per capita natural gas demand in the Middle Atlantic relative to New England and the South Atlantic is the higher share of multifamily housing units, which have higher thermal efficiency because of reduced surface area.

The constant term, which is indicative of the level of non-temperature sensitive natural gas demand (e.g. cooking), is greatest in the Middle Atlantic with lower, but similar, values observed in New England and the South Atlantic. All three census division have had no statistically significant change in non-temperature sensitive natural gas demand as indicated by the annual trend variable. Additionally, all census divisions show a positive correlation between hours of daylight and natural gas demand after controlling for heating degree-days. The price of natural gas is inversely and statistically significantly related to natural gas demand. In fact, the price elasticities estimated for each census division suggest that changes in price are associated with even larger changes in natural gas demand. For example, a 10% price increase in New England is associated with an 11.6% natural gas demand decrease. The residential natural gas model explains 96% of the historic variation in natural gas demand.

Tables 14-16 contain the individual state results for natural gas demand by the residential sector. In general, the state results coincide with the more aggregate census division results. The exceptions are Vermont in New England and Florida in the South Atlantic, both of which have natural gas demand sensitivities to heating degree-days that are considerably below the aggregate regional results.

Table 13. Census Divisions' Residential Natural Gas Regression Results with Static Sensitivities.

	New England Natural Gas per Capita (log)	Middle Atlantic Natural Gas per Capita (log)	South Atlantic Natural Gas per Capita (log)
Balance Point Temperature (F)	69	70	75
Constant	6.589106***	10.01914***	6.822041***
Annual Trend	-0.0041684	-0.0012321	0.0081518*
Heating Degree-days	0.0018558***	0.001032***	0.0020529***
Hours of Daylight	0.1202463***	0.0251477**	0.058441***
Natural Gas Price (log)	-1.164002***	-1.822938***	-1.096677***
R-squared	0.9606	0.9436	0.9463
DW (transformed)	1.995346	2.029014	2.051305

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 14. New England State Residential Natural Gas Regression Results with Static Sensitivities.

	Maine Natural Gas per Capita (log)	New Hampshire Natural Gas per Capita (log)	Vermont Natural Gas per Capita (log)	Massachusetts Natural Gas per Capita (log)	Connecticut Natural Gas per Capita (log)	Rhode Island Natural Gas per Capita (log)
Balance Point Temperature (F)	72	74	69	69	71	71
Constant	4.272977***	3.588339***	8.390273***	5.705712***	6.271425***	7.683329***
Annual Trend	0.0297346***	0.00040335	0.0259457*	-0.0015058	-0.0124086***	0.0014845
Heating Degree-days	0.001212***	0.0018722***	0.0008967***	0.0019963***	0.0018147***	0.0015913***
Hours of Daylight	0.0237753*	0.141305***	0.0227329	0.1315445***	0.1028403***	0.1027038***
Natural Gas Price (log)	-0.9887724***	-0.5431845***	-2.142445***	-0.702684***	-0.8795914***	-1.372798***
R-squared	0.9100	0.9510	0.8705	0.9417	0.9441	0.9622
DW (transformed)	1.926474	2.005672	2.044121	1.990570	2.017643	2.011909

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 15. Middle Atlantic States' Residential Natural Gas Regression Results with Static Sensitivities.

	New York Natural Gas per Capita (log)	New Jersey Natural Gas per Capita (log)	Pennsylvania Natural Gas per Capita (log)
Balance Point Temperature (F)	72	70	69
Constant	7.575968***	8.719395***	10.45552***
Annual Trend	0.0072796*	-0.0184311*	0.0062175
Heating Degree-days	0.0013802***	0.0013545***	0.0010243***
Hours of Daylight	0.0738031***	0.0253986	0.0329152***
Natural Gas Price (log)	-1.06891***	-1.190908***	-2.163234***
R-squared	0.9486	0.8975	0.9560
DW (transformed)	2.040327	1.932241	2.067021

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 16. South Atlantic States' Residential Natural Gas Regression Results with Static Sensitivities.

	Delaware Natural Gas per Capita (log)	Maryland Natural Gas per Capita (log)	Virginia Natural Gas per Capita (log)	West Virginia Natural Gas per Capita (log)	North Carolina Natural Gas per Capita (log)	South Carolina Natural Gas per Capita (log)	Georgia Natural Gas per Capita (log)	Florida Natural Gas per Capita (log)
Balance Point Temperature (F)	72	71	71	72	72	76	73	76
Constant	9.66037***	10.204***	6.42565***	9.6761***	9.08383***	9.23890***	7.10272***	9.68837***
Annual Trend	0.05495***	0.03492***	0.01806***	-0.018773	0.05982***	0.0276**	-0.01055*	0.03043***
Heating Degree-days	0.00101***	0.00093***	0.00194***	0.00125***	0.00129***	0.00182***	0.00195***	0.00043***
Hours of Daylight	0.0364104	-0.0039568	0.08133***	-0.027728	0.003906	-0.0056865	-0.033855*	0.0032563
Natural Gas Price (log)	-2.3043***	-1.9988***	-1.0327***	-1.581***	-2.0678***	-2.1768***	-0.2501***	-2.5366***
R-squared	0.8449	0.9013	0.9654	0.8416	0.8882	0.8143	0.9269	0.8583
DW (transformed)	2.125736	1.967369	2.029922	1.983399	1.944299	1.845597	1.956134	1.914004

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.1.3 Residential Heating Oil Results

Table 17 presents the residential heating oil regression results for the New England, Middle Atlantic, and South Atlantic census divisions. The results indicate balance point temperatures of 67˚F in New England, 69˚F in the Middle Atlantic, and 64˚F in the South Atlantic. The lower balance point in the South Atlantic is somewhat surprising because warmer regions typically have higher balance point temperatures. The result may be due to the relatively rare use of heating oil as a heating fuel in the South Atlantic.

The sensitivity of per capita heating oil sales to heating degree-days is similar in all three census divisions. A 100 unit increase in heating degree-days is associated with a 10.2% increase in heating oil sales in New England, a 8.0% increase in the Middle Atlantic, and a 10.0% increase in the South Atlantic.

Non-temperature-sensitive heating oil sales are highest in the Middle Atlantic, followed by New England, and then the South Atlantic. Moreover, non-temperature-sensitive heating oil sales have been declining in each census division as indicated by the annual trend variable.

In all census divisions hours of daylight are inversely related to heating oil sales, however the correlation is not statistically significant in the South Atlantic. Each additional hour of daylight in New England and the Middle Atlantic is associated with a 4.4% and 3.2% decrease, respectively, in heating oil sales. The price of heating oil is inversely related to heating oil sales, however, the relationship is only statistically significant in the South Atlantic census division where a 10% increase in the price of heating oil is associated with a 2.1% decrease in sales.

Tables 18-20 contain the individual state results for heating oil sales to the residential sector. For states in each census division the results suggest a wide range of balance point temperatures with New England ranging from 63˚F to 75˚F, the Middle Atlantic from 55˚F to 67˚F, and the South Atlantic from 55˚F to 78˚F. Likewise, per capita heating oil sensitivities to 100 unit increases in heating degree-days spanned from 7.0% to 12.4% in New England, 7.9% to 10.1% in the Middle Atlantic, and –0.1% to 11.9% in the South Atlantic.

Table 17. Census Divisions' Residential Heating Oil Regression Results with Static Sensitivities.

	New England Heating Oil per Capita (log)	Middle Atlantic Heating Oil per Capita (log)	South Atlantic Heating Oil per Capita (log)
Balance Point Temperature (F)	67	69	63
Constant	2.963866***	3.299559***	2.56825***
Annual Trend	-0.0152588***	-0.0366015***	-0.0220208***
Heating Degree-days	0.0010176***	0.0008007***	0.0010028***
Hours of Daylight	-0.0440788***	-0.0317605**	-0.002323
Heating Oil Price (log)	-0.042398	-0.1472147	-0.2053524**
Break Dummy Variable			October 1993 -0.3830***
R-squared	0.8191	0.7786	0.8165
DW (transformed)	2.103837	2.051863	2.240170

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 18. New England State's Residential Heating Oil Regression Results with Static Sensitivities.

	Maine Heating Oil per Capita (log)	New Hampshire Heating Oil per Capita (log)	Vermont Heating Oil per Capita (log)	Massachusetts Heating Oil per Capita (log)	Connecticut Heating Oil per Capita (log)	Rhode Island Heating Oil per Capita (log)
Balance Point Temperature (F)	74	75	74	69	63	66
Constant	2.738447***	2.70114***	0.7020221	3.442209***	1.466727	2.836038*
Annual Trend	0.0172484***	0.0040095	0.0198826*	-0.0383387***	0.0013449	-0.0187588**
Heating Degree-days	0.0007005***	0.0007689***	0.000774***	0.0011561***	0.0012435***	0.0011062***
Hours of Daylight	-0.0389996**	-0.0396014**	-0.0529569***	-0.0356098**	-0.0340301*	-0.0596795***
Heating Oil Price (log)	-0.0208007	-0.0339945	0.2841373	-0.1730799	0.2008838	0.1261469
R-squared	0.6134	0.6764	0.7554	0.7776	0.7028	0.6415
DW (transformed)	2.188953	2.202417	2.109109	2.267085	2.276978	2.251730

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 19. Middle Atlantic States' Residential Heating Oil Regression Results with Static Sensitivities.

	New York Heating Oil per Capita (log)	New Jersey Heating Oil per Capita (log)	Pennsylvania Heating Oil per Capita (log)
Balance Point Temperature (F)	67	63	55
Constant	1.25416*	2.868208**	2.8974***
Annual Trend	-0.0250026***	-0.0578432***	-0.0219863***
Heating Degree-days	0.0010103***	0.0009455***	0.0007935***
Hours of Daylight	-0.0269291**	-0.0353061**	-0.0279639**
Heating Oil Price (log)	0.1640104	0.1533779	-0.0757025
R-squared	0.8543	0.6821	0.6647
DW (transformed)	2.205353	2.234156	2.045837

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 20. South Atlantic States' Residential Heating Oil Regression Results with Static Sensitivities.

	Delaware Heating Oil per Capita (log)	Maryland Heating Oil per Capita (log)	Virginia Heating Oil per Capita (log)	West Virginia Heating Oil per Capita (log)	North Carolina Heating Oil per Capita (log)	South Carolina Heating Oil per Capita (log)	Georgia Heating Oil per Capita (log)	Florida Heating Oil per Capita (log)
Balance Point Temperature (F)	58	64	65	73	61	55	70	78
Constant	4.45495***	2.23712***	3.6062***	1.50493***	3.85284***	3.14414***	0.9179873	0.8201305
Annual Trend	-0.1323***	-0.0591***	-0.01048	0.02521***	-0.0342***	-0.02044**	-0.035***	-0.0272***
Heating Degree-days	0.00119***	0.00118***	0.00077***	-0.00001*	0.00075***	0.00098***	0.00032***	0.00044***
Hours of Daylight	-0.04984**	-0.0315**	-0.0053548	-0.048***	0.00073*	-0.00633	0.06692***	0.03395**
Heating Oil Price (log)	-0.0090723	0.0194954	-0.3532***	0.0924873	-0.4093***	-0.3134*	-0.104097	-0.12757
Break Dummy Variable			October 1993 -0.4995***	May 1990 0.27037***	October 1993 -0.55048	October 1993 -0.5878***		
R-squared	0.7924	0.8300	0.7622	0.5924	0.7146	0.5468	0.1487	0.3401
DW (transformed)	2.030076	2.104980	2.142873	2.082498	2.333523	2.409203	2.432064	2.213255

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.1.4 Commercial Electricity Results

Commercial electricity results for census divisions are detailed in Table 21. The statistical models imply balance point temperatures for commercial electricity of 51˚F in New England, 53˚F in the Middle Atlantic, and 52˚F in the South Atlantic. The similar balance point temperatures for commercial electricity suggest there is less adaptation to climate than was observed in the residential sector. The observed commercial balance point temperatures closely coincide with recommended balance points for commercial energy use analysis (Xenergy, 1993 quoted in Rosenthal and Gruenspecht, 1995).

The sensitivities of per employee electricity demand to heating degree-days are similar in New England and the Middle Atlantic with a 100 unit increase in heating degree-days associated with a 1.4% and 1.3% increase electricity demand, respectively. The sensitivity in the South Atlantic - where electricity is more often used as a heating source - is larger at 3.1%. Likewise, in New England and the Middle Atlantic the sensitivities of electricity to cooling degree-days are similar with a 100 unit increase in cooling degree-days associated with a 3.6% and 3.8% increase in electricity demand, respectively. The sensitivity in the South where commercial air-conditioning is near ubiquitous is, as expected, larger at 5.0%.

Non-temperature sensitive electricity loads, as represented by the constant, are similar and as the annual trend variable suggests have been increasing over time at rates of 0.5% to 1.3% per year. More hours of daylight are associated with less commercial electricity demand in each of the census divisions. An additional hour of daylight is correlated with a 1.2% decrease in electricity demand in New England, a 1.2% decrease in the Middle Atlantic, and a 2.2% decrease in the South Atlantic. The South Atlantic is the only census division showing a statistical relation between commercial electricity demand and the price of electricity. The results indicate that a 10% increase in the price of electricity is associated with a 3.7% decrease in electricity demand.

Tables 22-24 contain the individual state results for electricity demand by the commercial sector. The results for the individual states in general correspond to the more aggregate census region results of which the respective state is part. Balance point temperatures ranged from 45˚F to 52˚F in New England, 52˚F to 56˚F in the Middle Atlantic, and 51˚F to 57˚F in the South Atlantic. Electricity sensitivities to 100 unit increases in heating degree-days spanned from 0.9% to 2.1% in New England, 0.8% to 1.5% in the Middle Atlantic, and 1.4% to 3.2% in the South Atlantic. Electricity sensitivities to 100 unit increases in cooling degree-days spanned from 2.6% to 3.7% in New England, 3.3% to 4.9% in the Middle Atlantic, and 4.1% to 5.9% in the South Atlantic.

Table 21. Census Division Commercial Electricity Regression Results with Static Sensitivities.

	New England Electricity per Employee (log)	Middle Atlantic Electricity per Employee (log)	South Atlantic Electricity per Employee (log)
Balance Point Temperature (F)	51	53	52
Constant	6.239056***	6.19617***	7.208176***
Annual Trend	0.0047946***	0.0098353***	0.0128457***
Heating Degree-days	0.0001366***	0.000134***	0.0003071***
Cooling Degree-days	0.0003589***	0.0003834***	0.000499***
Hours of Daylight	-0.0115184***	-0.0122531***	-0.0221646***
Electricity Price (log)	0.0449095	0.0887011	-0.3679638***
Break Dummy Variable	Aug 1994, May-Dec 2000		Jan 1994, Jan 1996
R-squared	0.7645	0.6545	0.9583
DW (transformed)	1.961178	2.047163	1.966017

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 22. New England State Commercial Electricity Regression Results with Static Sensitivities.

	Maine Electricity per Employee (log)	New Hampshire Electricity per Employee (log)	Vermont Electricity per Employee (log)	Massachusetts Electricity per Employee (log)	Connecticut Electricity per Employee (log)	Rhode Island Electricity per Employee (log)
Balance Point Temperature (F)	46	45	50	52	50	50
Constant	6.008497***	6.462508***	6.382981***	6.512674***	6.612369***	6.696788***
Annual Trend	0.0143161***	0.0007318	0.0077054	0.0028981**	0.0017089	0.0044305**
Heating Degree-days	0.000116***	0.0002078***	0.0001069***	0.0001357***	0.0001391***	0.0000946**
Cooling Degree-days	0.0002565***	0.0002848***	0.0002764***	0.0003707***	0.0003291***	0.0003738***
Hours of Daylight	-0.0127602***	-0.0095873**	-0.0144944***	-0.0109411***	-0.0087999***	-0.0237502***
Electricity Price (log)	0.0706093	-0.2643717**	-0.044036	-0.0727395*	-0.0983829	-0.1323422**
Break Dummy Variable		August 1994				
R-squared	0.5893	0.8727	0.5542	0.6309	0.6986	0.6218
DW (transformed)	2.017574	1.955759	2.286934	2.027091	1.949299	2.070807

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 23. Middle Atlantic Commercial Electricity Regression Results with Static Sensitivities.

	New York Electricity per Employee (log)	New Jersey Electricity per Employee (log)	Pennsylvania Electricity per Employee (log)
Balance Point Temperature (F)	52	56	55
Constant	6.576895***	6.93549***	6.917164***
Annual Trend	0.0081355**	0.0034502***	0.0069098**
Heating Degree-days	0.0000798**	0.0000929***	0.0001495***
Cooling Degree-days	0.0003934***	0.0004898***	0.0003297***
Hours of Daylight	-0.02002***	-0.0096402***	-0.0063066
Electricity Price (log)	-0.0837889	-0.1789486***	-0.3274651***
R-squared	0.4582	0.8516	0.4508
DW (transformed)	2.336012	1.969433	1.813564

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 24. South Atlantic State Commercial Electricity Regression Results with Static Sensitivities.

	Delaware Electricity per Employee (log)	Maryland Electricity per Employee (log)	Virginia Electricity per Employee (log)	West Virginia Electricity per Employee (log)	North Carolina Electricity per Employee (log)	South Carolina Electricity per Employee (log)	Georgia Electricity per Employee (log)	Florida Electricity per Employee (log)
Balance Point Temperature (F)	53	53	55	53	51	57	54	57
Constant	6.8331***	5.9919***	6.3353***	7.1653***	7.2467***	7.4763***	7.5512***	7.5596***
Annual Trend	0.01052***	0.00972***	0.00986***	0.00625***	0.00955***	0.01579***	0.00574***	0.000677
Heating Degree-days	0.00021***	0.00026***	0.00025***	0.00032***	0.00022***	0.00014***	0.0003***	0.0002
Cooling Degree-days	0.00041***	0.00049***	0.00054***	0.00041***	0.00046***	0.00059***	0.00043***	0.00041***
Hours of Daylight	-0.0154***	-0.0104***	-0.00638**	-0.01416**	-0.0272***	-0.0336***	-0.00978	-0.0248***
Electricity Price (log)	-0.170538*	0.0415974	-0.0033478	-0.3224***	-0.26008**	-0.388***	-0.5605***	-0.4519***
Break Dummy Variable		Jan 1994, Jan 1996						
R-squared	0.5921	0.9819	0.8968	0.7318	0.7639	0.8560	0.8371	0.7944
DW (transformed)	1.926541	1.974212	1.935167	2.003598	1.975693	1.912540	2.268406	2.099053

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.1.5 Commercial Natural Gas Results

Table 25 contains the statistical results for commercial natural gas for the census divisions. Balance point temperatures are observed to be 67˚F in New England, 70˚F in the Middle Atlantic, and 75˚F in the South Atlantic. Significant sensitivities of per employee natural gas demand to changes in heating degree-days were detected in each census divisions. For a 100 unit increase in heating degree-days natural gas demand is estimated to increase by 9.9% in New England, 10.8% in the Middle Atlantic, and 13.4% in the South Atlantic.

The level of non-temperature sensitive natural gas demand is similar in each of the three census divisions, however both New England and the Middle Atlantic experienced increasing non-temperature sensitive natural gas demand over the period of analysis as indicated by the annual trend variables.

Hours of daylight for each month are positively correlated to natural gas use per employee with an additional hour of daylight associated with increase in natural gas use of 2.9% in New England, 2.8% in the Middle Atlantic, and 2.5% in the South Atlantic. The price of natural gas is positively related to natural gas use in New England and inversely related in the Middle Atlantic and South Atlantic.

Tables 26-28 contain the individual state results for natural gas demand by the commercial sector. Balance point temperatures ranged from 67˚F to 73˚F in New England, 65˚F to 72˚F in the Middle Atlantic, and 70˚F to 77˚F in the South Atlantic. Natural gas sensitivities to 100 unit increases in heating degree-days spanned from 10.9% to 17% in New England, 8.1% to 16.9% in the Middle Atlantic, and 5.1% to 15.6% in the South Atlantic. The state results generally correspond with the census division results with two exceptions. First in the Middle Atlantic, New York had a much lower sensitivity than New Jersey or Pennsylvania although it more closely matched the overarching census division's results. Second, Florida's natural gas sensitivity to heating degree-days was well below the South Atlantic's sensitivity.

Table 25. Census Division Commercial Natural Gas Regression Results with Static Sensitivities.

	New England Natural Gas per Employee (log)	Middle Atlantic Natural Gas per Employee (log)	South Atlantic Natural Gas per Employee (log)
Balance Point Temperature (F)	67	70	75
Constant	5.696337***	6.944525***	6.790315***
Annual Trend	0.0444618***	0.0486316***	0.0052906
Heating Degree-days	0.0009908***	0.0010813***	0.0013447***
Hours of Daylight	0.0295447**	0.0276985**	0.0252759*
Natural Gas Price (log)	0.2530662**	-0.2250131***	-0.418687*
Break Dummy Variable	Sept 1998 -0.4243046***		
R-squared	0.7988	0.8600	0.8681
DW (transformed)	2.172175	2.003684	1.883909

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 26. New England States' Commercial Natural Gas Regression Results with Static Sensitivities.

	Maine Natural Gas per Employee (log)	New Hampshire Natural Gas per Employee (log)	Vermont Natural Gas per Employee (log)	Massachusetts Natural Gas per Employee (log)	Connecticut Natural Gas per Employee (log)	Rhode Island Natural Gas per Employee (log)
Balance Point Temperature (F)	69	73	70	68	67	70
Constant	4.473958***	4.020171***	5.768253***	5.709204***	6.637622***	6.563751***
Annual Trend	0.0223813***	0.021311***	0.0136465	0.0778624***	0.0477615***	0.0555484***
Heating Degree-days	0.0012799***	0.0016979***	0.0010905***	0.0011751***	0.0011595***	0.0013528***
Hours of Daylight	0.0140091	0.1118085***	-0.0041963	0.0560222***	0.0338992**	0.0557721***
Natural Gas Price (log)	-0.0441298	-0.0996144	-0.1267906	0.0126219	-0.2459412**	-0.4261011***
Break Dummy Variable				Sept 1998 -0.706088***		
R-squared	0.9030	0.9486	0.8242	0.7860	0.7824	0.7891
DW (transformed)	1.942080	2.012959	2.087471	2.041995	2.182235	2.074568

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 27. Middle Atlantic State's Commercial Natural Gas Regression Results with Static Sensitivities.

	New York Natural Gas per Employee (log)	New Jersey Natural Gas per Employee (log)	Pennsylvania Natural Gas per Employee (log)
Balance Point Temperature (F)	65	69	72
Constant	7.612445***	6.271648***	5.833015***
Annual Trend	0.0813688***	0.0178582***	0.0008537
Heating Degree-days	0.0008065***	0.0016904***	0.0016261***
Hours of Daylight	-0.0004573	0.0977176***	0.0656546***
Natural Gas Price (log)	-0.3707337***	-0.2782592***	-0.0509223
R-squared	0.7387	0.9139	0.9628
DW (transformed)	1.867671	1.983316	1.996622

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 28. South Atlantic State's Commercial Natural Gas Regression Results with Static Sensitivities.

	Delaware Natural Gas per Employee (log)	Maryland Natural Gas per Employee (log)	Virginia Natural Gas per Employee (log)	West Virginia Natural Gas per Employee (log)	North Carolina Natural Gas per Employee (log)	South Carolina Natural Gas per Employee (log)	Georgia Natural Gas per Employee (log)	Florida Natural Gas per Employee (log)
Balance Point Temperature (F)	73	71	72	72	73	75	70	77
Constant	7.4702***	6.4101***	5.95879***	7.63498***	6.05513***	7.53331***	7.36064***	3.9407***
Annual Trend	0.031456**	0.05361***	0.01741***	-0.00079	-0.01311**	0.004446	-0.02386**	0.1413***
Heating Degree-days	0.00127***	0.00109***	0.00148***	0.00112***	0.00157***	0.00102***	0.00141***	0.00051***
Hours of Daylight	0.045307**	0.01983	0.06865***	0.01076	0.05914***	-0.0093***	-0.01709	-0.02237**
Natural Gas Price (log)	-1.1733***	-0.17108	-0.31279*	-0.2414***	-0.34374	-0.5686***	-0.1571***	0.02028
R-squared	0.7931	0.8051	0.9213	0.8743	0.8544	0.7993	0.8423	0.5828
DW (transformed)	2.213290	1.898577	2.050089	2.152760	1.917119	1.908382	1.718517	2.359974

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.2 Temporal Analysis Results with Dynamic Sensitivities

The statistical model presented in this section use the same balance point temperatures as determined with the iterative procedure used in section 6.1. The addition of the dynamic degree-day variables to the models of section 6.1 investigate whether or not a statistically significant time-varying component is observable in energy sensitivities to degree-days. For each heating degree-day and cooling degree-day variable in the models of section 6.1 an interaction term is created. The interaction term is the multiplicative product of the degree-day monthly total and annual trend variable and represents the annual percent change in demand sensitivities.

6.2.1 Residential Electricity Results

Residential electricity results for census divisions with the dynamic degree-day sensitivity variables are reported in Table 29. The balance point temperatures in both New England and the Middle Atlantic is 56˚F, whereas a balance point temperature of 63˚F is observed in the South Atlantic. The amount of electricity demanded at the balance point temperature, as indicated by the constant variables, is highest in the South Atlantic followed by the Middle Atlantic and then New England. None of the census divisions, as suggested by their annual trend variables, experience statistically significant changes in non-temperature sensitive electricity demand over the period of analysis. These findings are different than the static degree-day models, in which all three census divisions experienced increasing non-temperature sensitive electricity demands.

Similar to the results of the static degree-day analysis, electricity demand responses to changes in degree-days show considerable variation between census divisions. A 100 unit increase in heating degree-days is associated with a 4.4% increase in per capita electricity demand in New England, a 3.4% increase in the Middle Atlantic, and a 6.7% increase in the South Atlantic. The HDD dynamic sensitivity variable indicates no significant change in the sensitivity of electricity demand to heating degree-days.

The results indicate that at the start of the analysis period, a 100 unit increase in cooling degree-days is associated with a 2.8% increase in per capita electricity demand in New England, a 6.3% increase in the Middle Atlantic, and a 13.0% increase in the South Atlantic. In the New England and Middle Atlantic electricity demand sensitivities to cooling degree-days increased over the period of analysis at average annual rates of 0.4% and 0.3%, respectively. The observation of increasing electricity demand sensitivities to hot temperatures in cooler climates may be due to increasing penetration of air-conditioners. In contrast, the results for the South Atlantic – a region with a presently high prevalence of air-conditioning – suggest no change in electricity demand sensitivity to cooling degree-days.

The hours of daylight variable indicates that in each of the census divisions the more hours of daylight are associated with lower electricity demand per capita per month. Electricity demand decreases by 0.6%, 1.7%, and 1.7% for each additional hour of daylight in the New England, Middle Atlantic, and South Atlantic census divisions, respectively. The price of electricity is also inversely related to per capita electricity demand with higher monthly electricity prices associated with lower electricity demand per capita. A 10% increase in the price of electricity is associated with a 5.1% decrease in electricity demand in New England, a 8.1% decrease in the Middle Atlantic, and a 10.6% decrease in the South Atlantic.

The individual state responses are similar to the respective results at the census division level (see Tables 30-32). Electricity demand sensitivities to heating degree-days at the start of the analysis period ranged from 3.8% to 4.7% in New England states, 1.8% to 5.1% in Middle Atlantic states, and 1.6% to 9.6% in South Atlantic states. Two New England states, Maine and Vermont, experienced a statistically significant decreases in electricity sensitivity to heating degree-days. In the South Atlantic, Florida experienced a statistically significant increase in electricity sensitivity to heating degree-days.

Electricity demand sensitivities to cooling degree-days ranged from -0.3% to 4.8% in New England states, 4.1% to 11.1% in Middle Atlantic states, and 7.5% to 14.7% in South Atlantic states. The results indicate that all New England and Middle Atlantic states experienced increasing sensitivity to cooling degree-days with the exceptions of Rhode Island and New Jersey. Within the South Atlantic, in contrast, only Virginia and West Virginia experienced increasing electricity sensitivity to cooling degree-days. The increasing sensitivity observed in cooler New England and Middle Atlantic divisions, as discussed earlier, may be due to increasing prevalence of air-conditioners, whereas air-conditioning is largely saturated in the South Atlantic.

Table 29. Census Divisions' Residential Electricity Regression Results with Dynamic Degree-day Sensitivities.

	New England Electricity per Capita (log)	Middle Atlantic Electricity per Capita (log)	South Atlantic Electricity per Capita (log)
Balance Point Temperature (F)	56	56	63
Constant	6.441563***	7.132354***	7.783449***
Annual Trend	0.001378	0.0005863	0.00688
Heating Degree-days	0.0004421***	0.0003354***	0.0006742***
Dynamic HDD Sensitivity	0.000000099	0.00000438	0.0000122
Cooling Degree-days	0.0002753***	0.0006276***	0.0013011***
Dynamic CDD Sensitivity	0.0000428***	0.0000308***	0.0000151
Hours of Daylight	-0.0064528**	-0.0170682***	-0.0165223**
Electricity Price (log)	-0.5170007***	-0.806689***	-1.057305***
R-squared	0.8850	0.8113	0.8502
DW (transformed)	1.930371	1.781559	1.792178

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 30. New England States' Residential Electricity Regression Results with Dynamic Degree-day Sensitivity Variables.

	Maine Electricity per Capita (log)	New Hampshire Electricity per Capita (log)	Vermont Electricity per Capita (log)	Massachusetts Electricity per Capita (log)	Connecticut Electricity per Capita (log)	Rhode Island Electricity per Capita (log)
Balance Point Temperature (F)	53	55	55	55	57	55
Constant	5.922102***	5.805341***	5.635137***	5.722756***	5.960049***	5.822453***
Annual Trend	0.0025372	-0.010189***	0.0011995	0.0005276	-0.0011663	0.0129053**
Heating Degree-days	0.0004137***	0.0003774***	0.0004706***	0.0004182***	0.0004621***	0.0004649***
Dynamic HDD Sensitivity	-0.0000111**	0.0000081	-0.0000097***	0.00000383	0.0000107*	-0.0000132
Cooling Degree-days	-0.0000262	0.00000997	0.0001406*	0.0002194***	0.0004754***	0.0004004***
Dynamic CDD Sensitivity	0.0000239**	0.0000623***	0.0000328***	0.0000421***	0.0000502***	0.0000273*
Hours of Daylight	0.0061953*	0.00060102	-0.0060754**	-0.0085415**	-0.010962***	-0.0151039**
Electricity Price (log)	-0.2915544***	-0.2313105***	-0.0730131	-0.2049529**	-0.2254656**	-0.2690629***
R-squared	0.8024	0.8165	0.9320	0.8195	0.8820	0.5913
DW (transformed)	1.94	2.01	1.80	1.88	1.99	1.99

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 31. Middle Atlantic States' Residential Electricity Regression Results with Dynamic Degree-day Sensitivity Variables.

	New York Electricity per Capita (log)	New Jersey Electricity per Capita (log)	Pennsylvania Electricity per Capita (log)
Balance Point Temperature (F)	53	57	60
Constant	7.027249***	5.40719***	6.228174***
Annual Trend	0.0031148	0.0071768*	0.0035303
Heating Degree-days	0.0001872***	0.00043***	0.0005089***
Dynamic HDD Sensitivity	0.00000809	-0.00000247	0.00000113
Cooling Degree-days	0.0004108***	0.0011102***	0.0006736***
Dynamic CDD Sensitivity	0.0000233**	0.0000204*	0.0000502***
Hours of Daylight	-0.0264677***	-0.-229307***	0.0015008
Electricity Price (log)	-0.726956***	-0.0177323	-0.4519096***
R-squared	0.6330	0.8782	0.8556
DW (transformed)	1.63065	1.882204	1.886842

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 32. South Atlantic States' Residential Electricity Regression Results with Dynamic Degree-day Sensitivity Variables.

	Delaware Electricity per Capita (log)	Maryland Electricity per Capita (log)	Virginia Electricity per Capita (log)	West Virginia Electricity per Capita (log)	North Carolina Electricity per Capita (log)	South Carolina Electricity per Capita (log)	Georgia Electricity per Capita (log)	Florida Electricity per Capita (log)
Balance Point Temperature (F)	56	60	61	62	61	63	61	68
Constant	7.3937***	5.5115***	5.9532***	6.307***	7.3956***	9.6611***	6.1602***	8.443***
Annual Trend	0.00957	0.006224	0.006183*	0.0115***	0.0050001	0.011555	0.0109***	0.007983*
Heating Degree-days	0.0005987 ***	0.0006782 ***	0.000957* **	0.0007082 ***	0.0008069 ***	0.0006767 ***	0.0007083 ***	0.0001552
Dynamic HDD Sensitivity	0.0000033	0.000011	0.0000016	0.000008	0.0000044	0.000004	0.000012	0.00005**
Cooling Degree-days	0.0007486 ***	0.0009995 ***	0.0012076 ***	0.0008734 ***	0.0009827 ***	0.0010337 ***	0.0014765 ***	0.0011658 ***
Dynamic CDD Sensitivity	0.000012	0.000026*	0.0000284 ***	0.0000387 **	0.000019	0.0000103	0.00002*	0.0000095
Hours of Daylight	-0.013001	0.001967	0.007129	0.007613	-0.01664	-0.18621	-0.026***	-0.051***
Electricity Price (log)	-0.858***	-0.06635	-0.2839**	-0.516***	-0.785***	-2.016***	-0.20199	-1.051***
R-squared	0.5848	0.8535	0.9435	0.8976	0.7082	0.7287	0.9311	0.8772
DW (transformed)	1.80	1.91	1.90	2.05	1.82	1.75	1.97	1.94

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.2.2 Residential Natural Gas Results

Table 33 presents the residential natural gas regression results with the dynamic degree-day sensitivity variables for the New England, Middle Atlantic, and South Atlantic census divisions. Tables 34-36 contain the individual state results. The inclusion of dynamic degree-day sensitivity variables into the statistical models provides little additional explanatory power (see R-squared values) compared to the models using the static degree-day sensitivity variables (see 6.1.2). New England is the only census division to have residential natural gas demand become increasingly sensitive to heating degree-days. At the state-level Maine, New Hampshire, Connecticut, and New Jersey experience increased natural gas demand sensitivity to heating degree-days, which could be attributable to increased natural gas availability and use in these regions.

Table 33. Census Divisions' Residential Natural Gas Regression Results with Dynamic Degree-day Sensitivity Variables.

	New England Natural Gas per Capita (log)	Middle Atlantic Natural Gas per Capita (log)	South Atlantic Natural Gas per Capita (log)
Balance Point Temperature (F)	69	70	75
Constant	6.548719***	10.03264***	6.783279***
Annual Trend	-0.0137323***	-0.0093437	0.0039449
Heating Degree-days	0.0017626***	0.0009422***	0.002***
Dynamic HDD Sensitivity	0.0000156**	0.0000138*	0.00000988
Hours of Daylight	0.1227497***	0.0258696**	0.059315***
Natural Gas Price (log)	-1.132027***	-1.808372***	-1.071011***
R-squared	0.9634	0.9442	0.9463
DW (transformed)	2.00	2.04	2.06

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 34. New England State Residential Natural Gas Regression Results with Dynamic Degree-day Sensitivity Variables.

	Maine Natural Gas per Capita (log)	New Hampshire Natural Gas per Capita (log)	Vermont Natural Gas per Capita (log)	Massachusetts Natural Gas per Capita (log)	Connecticut Natural Gas per Capita (log)	Rhode Island Natural Gas per Capita (log)
Balance Point Temperature (F)	72	74	69	69	71	71
Constant	4.175779***	3.607452***	8.41255***	5.673244***	6.796895***	7.612935***
Annual Trend	0.0128424	-0.0107746	0.0207716	-0.0086349	-0.037533***	-0.00339
Heating Degree-days	0.001096***	0.0017677***	0.0008525***	0.0019218***	0.0015493***	0.001554***
Dynamic HDD Sensitivity	0.0000203**	0.0000175**	0.00000688	0.0000119	0.0000379***	0.0000079
Hours of Daylight	0.0264058**	0.144656***	0.0230391	0.1330629***	0.109598***	0.1046583***
Natural Gas Price (log)	-0.9081192***	-0.5289046***	-2.138453***	-0.674798***	-1.075742***	-1.339573***
R-squared	0.9158	0.9550	0.8697	0.9427	0.9602	0.9632
DW (transformed)	1.92	2.00	2.03	1.99	1.99	2.01

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 35. Middle Atlantic States' Residential Natural Gas Regression Results with Dynamic Degree-day Sensitivity Variable.

	New York Natural Gas per Capita (log)	New Jersey Natural Gas per Capita (log)	Pennsylvania Natural Gas per Capita (log)
Balance Point Temperature (F)	72	70	69
Constant	7.543218***	9.017149***	10.48339***
Annual Trend	0.0037549	-0.0454856***	0.000289
Heating Degree-days	0.0013544***	0.0010476***	0.0009443***
Dynamic HDD Sensitivity	0.0000054	0.0000436***	0.0000109
Hours of Daylight	0.0754935***	0.0293706*	0.0312655**
Natural Gas Price (log)	-1.05533***	-1.274771***	-2.145561***
R-squared	0.9494	0.9066	0.9544
DW (transformed)	2.04	2.05	2.06

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 36. South Atlantic States' Residential Natural Gas Regression Results with Dynamic Degree-day Sensitivity Variable.

	Delaware Natural Gas per Capita (log)	Maryland Natural Gas per Capita (log)	Virginia Natural Gas per Capita (log)	West Virginia Natural Gas per Capita (log)	North Carolina Natural Gas per Capita (log)	South Carolina Natural Gas per Capita (log)	Georgia Natural Gas per Capita (log)	Florida Natural Gas per Capita (log)
Balance Point Temperature (F)	72	71	71	72	72	76	73	76
Constant	9.6371***	10.139***	6.2709***	9.6938***	9.0837***	9.2657***	7.1144***	9.714***
Annual Trend	0.04628**	0.02987**	0.0093	-0.02493	0.05986***	0.02583	-0.0139*	0.03426***
Heating Degree-days	0.00093 ***	0.0008956 ***	0.0018778 ***	0.0011814 ***	0.0012866* **	0.0017855 ***	0.001889 ***	0.0005572 ***
Dynamic HDD Sensitivity	0.0000137	0.00000786	0.0000167*	0.0000101	-0.0000001	-0.0000042	0.000009	-0.0000197
Hours of Daylight	0.0378374	-0.002851	0.08762***	-0.0276728	0.0039018	-0.0061617	-0.034055*	0.003322
Natural Gas Price (log)	-2.275***	-1.9595***	-0.977***	-1.5692***	-2.0679***	-2.1805***	-0.2434***	-2.5590***
R-squared	0.8448	0.9012	0.9684	0.8410	0.8874	0.8129	0.9268	0.8582
DW (transformed)	2.13	1.98	2.02	1.99	1.94	1.85	1.96	1.92

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.2.3 Residential Heating Oil Results

Table 37 presents the residential heating oil regression results with the inclusion of the dynamic degree-day sensitivity variables for the New England, Middle Atlantic and South Atlantic census divisions. Tables 38-40 contain the individual state results for heating oil sales to the residential sector. The specification of the census division and state statistical models with the inclusion of the dynamic degree-day variable results in only minor changes compared to the models that used the static degree-day variables (refer to section 6.1.3). The findings suggest that heating oil demand responses have been relatively stable over the period of analysis. No census division as a whole, and only the individual states of New Hampshire, Vermont, and Delaware experienced a statistically significant increase in heating oil sensitivity to heating degree-days.

Table 37. Census Divisions' Residential Heating Oil Regression Results with Dynamic Sensitivity Variable.

	New England Heating Oil per Capita (log)	Middle Atlantic Heating Oil per Capita (log)	South Atlantic Heating Oil per Capita (log)
Balance Point Temperature (F)	67	69	63
Constant	3.039566***	3.374128***	2.538501***
Annual Trend	-0.0223233***	-0.0393845***	-0.0211886***
Heating Degree-days	0.0008966***	0.0007536***	0.0010413***
Dynamic HDD Sensitivity	0.000012*	0.00000476	-0.00000415
Hours of Daylight	-0.0431834***	-0.0314674**	-0.0026944
Heating Oil Price (log)	-0.0461464	-0.1585222	-0.199409**
Break Dummy Variable			October 1993 -0.3827404***
R-squared	0.8219	0.7783	0.8177
DW (transformed)	2.13	2.06	2.27

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 38. New England State's Residential Heating Oil Regression Results with Dynamic Degree-day Sensitivity Variable.

	Maine Heating Oil per Capita (log)	New Hampshire Heating Oil per Capita (log)	Vermont Heating Oil per Capita (log)	Massachusetts Heating Oil per Capita (log)	Connecticut Heating Oil per Capita (log)	Rhode Island Heating Oil per Capita (log)
Balance Point Temperature (F)	74	75	74	69	63	66
Constant	2.784104***	2.970994***	0.9474459	3.524164***	1.586592	2.904325*
Annual Trend	0.0118898	-0.0202053***	0.0002126	-0.0460959***	-0.0059554	-0.0250001***
Heating Degree-days	0.0006395***	0.0005038***	0.0005672***	0.001029***	0.001083***	0.0009772***
Dynamic HDD Sensitivity	0.00000595	0.0000273***	0.0000204***	0.0000126	0.0000163	0.0000127
Hours of Daylight	-0.0386377**	-0.0354663**	-0.0520773***	-0.0348096**	-0.0324761*	-0.0588238***
Heating Oil Price (log)	-0.0197779	-0.0534228	0.2704059	-0.1762256	0.185735	0.1226284
R-squared	0.6146	0.7197	0.7658	0.7793	0.7081	0.6434
DW (transformed)	2.19	2.21	2.22	2.28	2.29	2.25

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 39. Middle Atlantic States' Residential Heating Oil Regression Results with Dynamic Degree-day Sensitivity Variable.

	New York Heating Oil per Capita (log)	New Jersey Heating Oil per Capita (log)	Pennsylvania Heating Oil per Capita (log)
Balance Point Temperature (F)	67	63	55
Constant	1.276037*	2.923872**	2.953542***
Annual Trend	-0.0279247***	-0.0617481***	-0.0251582***
Heating Degree-days	0.0009553***	0.0008513***	0.0006885***
Dynamic HDD Sensitivity	0.00000556	0.00000972	0.0000108
Hours of Daylight	-0.0263074**	-0.0342613**	-0.027147**
Heating Oil Price (log)	0.1638453	0.1464287	-0.0837949
R-squared	0.8559	0.6824	0.6659
DW (transformed)	2.21	2.24	2.06

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 40. South Atlantic States' Residential Heating Oil Regression Results with Dynamic Sensitivity Variable.

	Delaware Heating Oil per Capita (log)	Maryland Heating Oil per Capita (log)	Virginia Heating Oil per Capita (log)	West Virginia Heating Oil per Capita (log)	North Carolina Heating Oil per Capita (log)	South Carolina Heating Oil per Capita (log)	Georgia Heating Oil per Capita (log)	Florida Heating Oil per Capita (log)
Balance Point Temperature (F)	58	64	65	73	61	55	70	78
Constant	4.7464***	2.4421***	3.5388***	1.4465***	3.8321***	3.1478***	0.89088	0.74242
Annual Trend	-0.1428***	-0.0646***	-0.0088	0.02923***	-0.0337***	-0.02055**	-0.0341***	-0.0235***
Heating Degree-days	0.0006115*	0.00105***	0.00081***	-0.000035	0.00078***	0.00097***	0.00034***	0.00063***
Dynamic HDD Sensitivity	0.000044**	0.0000146*	-0.0000048	-0.0000067	-0.0000023	0.00000116	-0.0000025	-0.000018*
Hours of Daylight	-0.04815**	-0.02899*	-0.00589	-0.0493***	0.000576	-0.006278	0.0667***	0.03285**
Heating Oil Price (log)	-0.049019	-0.021971	-0.3403***	0.10045	-0.4053***	-0.31411*	-0.09923	-0.115589
Break Dummy Variable			October 1993 -0.4983***	May 1990 0.27211***	October 1993 -0.5503***	October 1993 -0.5878***		
R-squared	0.7996	0.8395	0.7603	0.5969	0.7124	0.5448	0.1452	0.3501
DW (transformed)	2.03	2.09	2.15	2.08	2.34	2.41	2.43	2.22

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.2.4 Commercial Electricity Results

Commercial electricity results for census divisions are detailed in Table 41 and the results for individual states are in Tables 42-44. Unlike the residential sector, the introduction of dynamic degree-day variables into the commercial electricity models does not significantly improve the explanatory power of the model, nor suggest any time-varying component of the electricity sensitivity to degree-days. Consequently, the statistical results closely match the results of the static degree-day sensitivity models because the dynamic degree-day variables are not significantly different from zero.

Table 41. Census Division Commercial Electricity Regression Results with Dynamic Degree-day Sensitivity Variables.

	New England Electricity per Employee (log)	Middle Atlantic Electricity per Employee (log)	South Atlantic Electricity per Employee (log)
Balance Point Temperature (F)	51	53	57
Constant	6.265608***	6.138823***	7.244275***
Annual Trend	0.0033589	0.01181***	0.0094037***
Heating Degree-days	0.0001444***	0.0001684***	0.0002273***
Dynamic HDD Sensitivity	-0.00000131	-0.00000481	0.0000116
Cooling Degree-days	0.0003005***	0.0004067***	0.0004596***
Dynamic CDD Sensitivity	0.00000901*	-0.00000375	0.00000608*
Hours of Daylight	-0.011657***	-0.0120244***	-0.0223885***
Electricity Price (log)	0.0372962	0.1090779	-0.3741309***
Break Dummy Variable	Aug 1994, May-Dec 2000		Jan 1994, Jan 1996
R-squared	0.7863	0.6526	0.9602
DW (transformed)	1.94	2.04	1.96

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 42. New England State Commercial Electricity Regression Results with Dynamic Degree-day Sensitivity Variables.

	Maine Electricity per Employee (log)	New Hampshire Electricity per Employee (log)	Vermont Electricity per Employee (log)	Massachusetts Electricity per Employee (log)	Connecticut Electricity per Employee (log)	Rhode Island Electricity per Employee (log)
Balance Point Temperature (F)	46	45	50	52	50	50
Constant	6.065882***	6.424375***	6.454641***	6.506679***	6.644094***	6.653693***
Annual Trend	0.0166399***	-0.0033598	0.009388***	0.0011901	0.0024943	0.0041957
Heating Degree-days	0.0001837***	0.0001743***	0.0001756***	0.0001467***	0.0001839***	0.0001509*
Dynamic HDD Sensitivity	-0.0000089	0.00000534	-0.00000905**	-0.00000149	-0.0000069	-0.00000911
Cooling Degree-days	0.0002457***	0.0002085***	0.0002152***	0.0002945***	0.0003194***	0.000309***
Dynamic CDD Sensitivity	0.00000163	0.0000121*	0.0000101	0.0000115*	0.00000129	0.00001
Hours of Daylight	-0.0129833***	-0.0096566**	-0.0155255***	-0.0108835***	-0.0087862***	-0.0242681***
Electricity Price (log)	0.0349479	-0.2334512**	-0.0806899*	-0.0644584	-0.1166239	-0.1065138*
Break Dummy Variable		August 1994				
R-squared	0.6073	0.8766	0.5892	0.6490	0.7152	0.6475
DW (transformed)	2.00	1.94	2.42	2.01	1.94	2.04

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 43. Middle Atlantic Commercial Electricity Regression Results with Dynamic Degree-day Sensitivity Variables.

	New York Electricity per Employee (log)	New Jersey Electricity per Employee (log)	Pennsylvania Electricity per Employee (log)
Balance Point Temperature (F)	52	56	55
Constant	6.547766***	6.931605***	6.934741***
Annual Trend	0.0096546**	0.0062805***	0.0059862
Heating Degree-days	0.0000909	0.0001582***	0.0001548**
Dynamic HDD Sensitivity	-0.00000158	-0.00001**	-0.000000742
Cooling Degree-days	0.0004297***	0.0005091***	0.0002909***
Dynamic CDD Sensitivity	-0.00000576	-0.00000276	0.00000597
Hours of Daylight	-0.0198865***	-0.0097919***	-0.0062942
Electricity Price (log)	-0.0756903	-0.1853849***	-0.334031***
R-squared	0.4518	0.8692	0.4444
DW (transformed)	2.33	1.96	1.81

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 44. South Atlantic State Commercial Electricity Regression Results Dynamic Degree-day Sensitivity Variables.

	Delaware Electricity per Employee (log)	Maryland Electricity per Employee (log)	Virginia Electricity per Employee (log)	West Virginia Electricity per Employee (log)	North Carolina Electricity per Employee (log)	South Carolina Electricity per Employee (log)	Georgia Electricity per Employee (log)	Florida Electricity per Employee (log)
Balance Point Temperature (F)	53	53	55	53	51	57	54	57
Constant	6.8382***	5.9512***	6.3099***	7.1535***	7.2379***	7.4942***	7.5401***	7.577***
Annual Trend	0.000937**	0.01079***	0.01154***	0.00395	0.00718**	0.0131***	0.00692*	-0.00158
Heating Degree-days	0.000182**	0.00033***	0.00031***	0.0003***	0.000193*	0.000081	0.00036***	-0.00042
Dynamic HDD Sensitivity	0.0000037	-0.0000099	-0.0000079	0.00000238	0.00000444	0.00000883	-0.0000091	0.000076**
Cooling Degree-days	0.00039***	0.00047***	0.00055***	0.00036***	0.00042***	0.00055***	0.00044***	0.00039***
Dynamic CDD Sensitivity	0.00000213	0.00000224	-0.000001	0.00000915	0.00000589	0.0000062	-0.0000015	0.00000335
Hours of Daylight	-0.0155***	-0.0106***	-0.00636**	-0.0148***	-0.0275***	-0.034***	-0.009456	-0.0258***
Electricity Price (log)	-0.16895*	0.062555	0.004902	-0.3007***	-0.24432**	-0.3852***	-0.561***	-0.4462***
Break Dummy Variable		Jan 1994, Jan 1996						
R-squared	0.5862	0.9845	0.8998	0.7365	0.7662	0.8565	0.8341	0.8021
DW (transformed)	1.93	1.99	1.94	1.99	1.97	1.91	2.28	2.12

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.2.5 Commercial Natural Gas Results

Table 45 contains the statistical results for commercial natural gas demand for the census divisions. Tables 46-48 contain the individual state results for natural gas demand by the commercial sector. The dynamic heating degree-day sensitivity variables indicate no statistically significant changes in commercial natural gas demand sensitivities to heating degree-days over the period of analysis. As a consequence, the results closely match those reported in section 6.1.5.

Table 45. Census Divisions' Commercial Natural Gas Regression Results with Dynamic Degree-day Sensitivity Variable.

	New England Natural Gas per Employee (log)	Middle Atlantic Natural Gas per Employee (log)	South Atlantic Natural Gas per Employee (log)
Balance Point Temperature (F)	67	70	72
Constant	5.709687***	6.693632***	6.783715***
Annual Trend	0.0404882***	0.060226***	0.0011527
Heating Degree-days	0.0009469***	0.0012794***	0.0012593***
Dynamic HDD Sensitivity	0.00000652	-0.0000224***	0.00000997
Hours of Daylight	0.0300715**	0.0354323***	0.0223685
Natural Gas Price (log)	0.2564293**	-0.1981577**	-0.3724314*
Break Dummy Variable	Sept 1998 -0.42455***		
R-squared	0.7980	0.8869	0.8635
DW (transformed)	2.18	2.02	1.88

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 46. New England States' Commercial Natural Gas Regression Results with Dynamic Sensitivity Variable.

	Maine Natural Gas per Employee (log)	New Hampshire Natural Gas per Employee (log)	Vermont Natural Gas per Employee (log)	Massachusetts Natural Gas per Employee (log)	Connecticut Natural Gas per Employee (log)	Rhode Island Natural Gas per Employee (log)
Balance Point Temperature (F)	69	73	70	68	67	70
Constant	4.5156***	4.083712***	5.869688***	5.711448***	6.629964***	6.375523***
Annual Trend	0.0022069	0.0071177	0.0048537	0.0772917***	0.048252***	0.0141922
Heating Degree-days	0.0011204***	0.0015892***	0.0009972***	0.0011685***	0.0011666***	0.0010479***
Dynamic HDD Sensitivity	0.0000259***	0.0000178***	0.00001	0.000000859	-0.0000011	0.0000495***
Hours of Daylight	0.0182791	0.1146946***	-0.0085424	0.055999***	0.0338963**	0.0650191***
Natural Gas Price (log)	-0.0295361	-0.1056923*	-0.1099677	0.0138464	-0.2436777**	-0.26603**
Break Dummy Variable				Sept 1998 -0.7063535***		
R-squared	0.9144	0.9545	0.8150	0.7843	0.7811	0.8494
DW (transformed)	1.94	2.04	2.07	2.04	2.18	2.02

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 47. Middle Atlantic State's Commercial Natural Gas Regression Results with Dynamic Degree-day Sensitivity Variable.

	New York Natural Gas per Employee (log)	New Jersey Natural Gas per Employee (log)	Pennsylvania Natural Gas per Employee (log)
Balance Point Temperature (F)	65	69	72
Constant	7.322612***	6.364575***	5.852852***
Annual Trend	0.0963837***	0.0038316	-0.004002
Heating Degree-days	0.001084***	0.0015144***	0.001577***
Dynamic HDD Sensitivity	-0.0000405***	0.0000295***	0.00000716
Hours of Daylight	0.0010094	0.1019453***	0.066001***
Natural Gas Price (log)	-0.2814787***	-0.3134693***	-0.0466467
R-squared	0.7817	0.9291	0.9632
DW (transformed)	1.95	1.96	2.00

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

Table 48. South Atlantic State's Commercial Natural Gas Regression Results with Dynamic Degree-day Sensitivity Variable.

	Delaware Natural Gas per Employee (log)	Maryland Natural Gas per Employee (log)	Virginia Natural Gas per Employee (log)	West Virginia Natural Gas per Employee (log)	North Carolina Natural Gas per Employee (log)	South Carolina Natural Gas per Employee (log)	Georgia Natural Gas per Employee (log)	Florida Natural Gas per Employee (log)
Balance Point Temperature (F)	73	71	72	72	73	75	70	77
Constant	7.469***	6.4191***	5.9714***	7.3064***	6.0663***	6.1616***	7.46138***	3.7453***
Annual Trend	0.033038**	0.057***	0.01825***	0.00938	-0.0251***	0.0019	-0.0362***	0.1503***
Heating Degree-days	0.00128***	0.00113***	0.00149***	0.00131***	0.0014***	0.00139***	0.00113***	0.00059***
Dynamic HDD Sensitivity	-0.0000027	-0.0000059	-0.0000014	-0.00002**	0.000027**	0.0000017	0.00004***	-0.000013
Hours of Daylight	0.045207**	0.01969	0.06841***	0.024528	0.06304***	0.06368***	-0.018925	-0.02282**
Natural Gas Price (log)	-1.1778***	-0.188645	-0.32201*	-0.21046**	-0.333892	-0.3363**	-0.1523***	-0.006302
R-squared	0.7919	0.8047	0.9206	0.8955	0.8646	0.8424	0.8495	0.5835
DW (transformed)	2.21	1.90	2.05	2.09	1.93	1.98	1.74	2.35

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

6.3 Geographic Analysis Results

In this section, the state-level findings of sections 6.1 and 6.2 are compared with each other in order to discern adaptation by energy user to local climatic conditions and the implications for energy demand responses to climate change. If, as is hypothesized, energy users adapt to effectively meet space-conditioning desires under current climatic conditions through technological and behavioral adjustments, then climatic change may induce further adaptation to the new climatic characteristics. These further adaptations would alter the V-shaped energy demand-temperature function, which in turn suggests that projections of future energy demand responses to climate change scenarios that include adaptation would be different from responses produced by models that neglect adaptation. Therefore, this study employs a geographic analysis to develop a metric of adaptation, which is then incorporated into energy demand responses to climate change scenarios.

In this study, adaptation to climate is quantified by examining differences in balance point temperatures. Adaptation to climate change is subsequently modeled by altering the balance point temperature of an energy system to the resultant temperature change of the climate change scenario. If it is found that balance point temperatures do in fact vary by climate, as modeled in this study with long-term average temperature, then balance point temperature can be regarded as a metric of potential long-term adaptation to climate change. A balance point temperature, as detailed in section 4.2.1.1, is determined by desired indoor temperature and the thermal efficiency of the building shell, both of which are forms of adaptation to climate. Hence, a correlation between balance point temperatures and population-weighted average temperatures quantitatively reflect adaptation by energy users to climate.

Figures 32-36 show the relationships between average annual population-weighted temperature and balance point temperature for residential electricity, residential natural gas, residential heating oil, commercial electricity, and commercial natural gas, respectively, for the seventeen states investigated in this study. With the exception of residential heating oil, the figures suggest a positive correlation between average annual population-weighted temperature and the balance point temperature of the energy type. The positive correlation supports the hypotheses (1) that energy systems in warmer climates have higher balance point temperatures and (2) that energy users adapt to climatic conditions to efficiently meet space-conditioning preferences.

Figure 32. States' Residential Electricity Balance Point Temperature and Population-weighted Average Temperature.

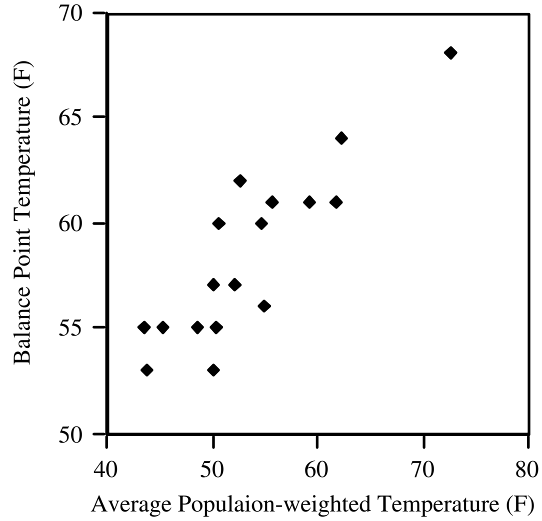


Figure 33. States' Residential Natural Gas Balance Point Temperature and Population-weighted Average Temperature.

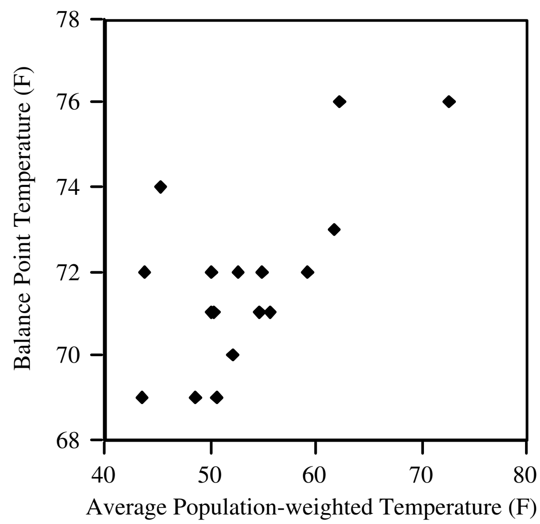


Figure 34. States' Residential Heating Oil Balance Point Temperature and Population-weighted Average Temperature.

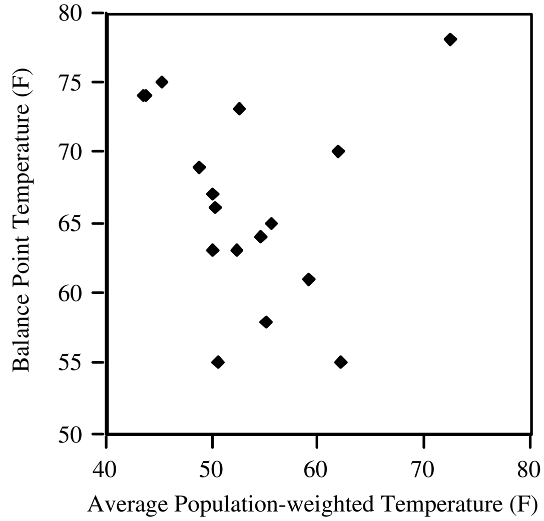


Figure 35. States' Commercial Electricity Balance Point Temperature and Population-weighted Average Temperature.

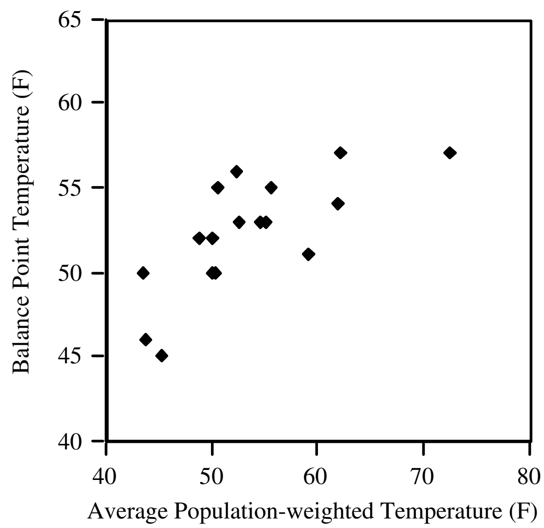
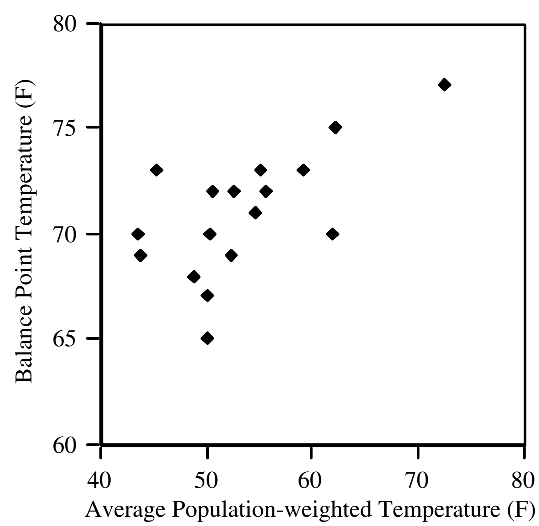


Figure 36. States' Commercial Natural Gas Balance Point Temperature and Population-weighted Average Temperature.



To create metrics of adaptation to climatic change for each energy type statistical models are developed to quantify the relation between a state's balance point temperature and its average annual population-weighted temperature. In the statistical models, balance point temperature is estimated as a function of a constant and population-weighted temperature. Table 49 details the statistical findings by sector and energy type.

Table 49. State Energy Type Balance Point Temperature (BPT) Models.

	Residential Electricity BPT	Residential Natural Gas BPT	Residential Heating Oil BPT	Commercial Electricity BPT	Commercial Natural Gas BPT
Average Temperature	0.4907***	0.1836***	-0.1012	0.3353***	0.2517***
Constant	32.2117***	61.9619***	71.8753***	34.3935***	57.5009***
R-squared	0.7660	0.4167	0.0116	0.5265	0.4006

*** Statistically Significant at the 1% level
** Statistically Significant at the 5% level
* Statistically Significant at the 10% level

The correlation between balance point temperature and average annual population-weighted temperature are strongest in the electricity demand models with average temperature explaining 76% and 53% of the variation in the residential and commercial sector models, respectively. The natural gas demand models explain 42% and 40% of the variation in the residential and commercial sectors, respectively. No relationship is observable between residential heating oil's balance point temperature and population-weighted temperature.

The average temperature coefficient of each statistical model indicates the difference in balance point temperature associated with a 1°F difference in average annual population-weighted temperature. For example, the slope of relation between average annual population-weighted temperature and residential electricity balance point temperature suggests that for a 1°F difference in average temperature between states a 0.49°F difference is expected in balance point temperature.

The statistically derived differences in balance point temperatures associated with differences in average annual population-weighted temperature are used in this study as metrics to change balance point temperatures within states in response to climate change scenarios. Energy demand responses to climate change scenarios that include adaptation are developed for the states of Massachusetts and Georgia. These two states were chosen as examples to investigate adaptation to climate change because they represent a cooler climate (Massachusetts) and a warmer climate (Georgia). For a given climate change scenario each state's balance point temperature is specified based on (1) the current balance point temperature of an energy type observed in the respective state and (2) the change predicted by the inter-state statistical analysis of the population-weighted average temperature and balance point temperatures relationship.

Adaptive energy demand responses to climate change scenarios for Massachusetts and Georgia are presented in Section 7.2. The results of climate change impacts on energy demand with adaptation are compared to the results from the same climate scenario without adaptation.

7. Energy Demand Responses to Climate Scenarios

In this section, energy demand responses to climate scenarios without adaptation to climate (section 7.1) and with adaptation to climate (section 7.2) are presented and discussed. The energy demand responses detailed in sections 7.1 are based on the temporal analysis whereas the responses in section 7.2 are based on a synthesis of the temporal analysis and geographic analysis.

7.1 Energy Demand Responses to Climate Scenarios Without Adaptation

The statistical models developed in sections 6.1 and 6.2 in conjunction with climate scenarios are used to estimate energy responses in the year 2005. For each state and census division three climate scenarios are developed: a scenario with monthly temperature normals of the 1971-2001 period, a scenario with average monthly temperatures 2°F higher than the normals, and a scenario with average monthly temperatures 4°F higher than the normals. State and census divisional degree-days for each climate scenario are estimated using the optimal balance point temperature observed in section 6.1. Degree-day estimation is performed with the Thom methodology and retains the historic monthly temperature standard deviations. Monthly price parameters are held at the 1991 to 2001 averages.

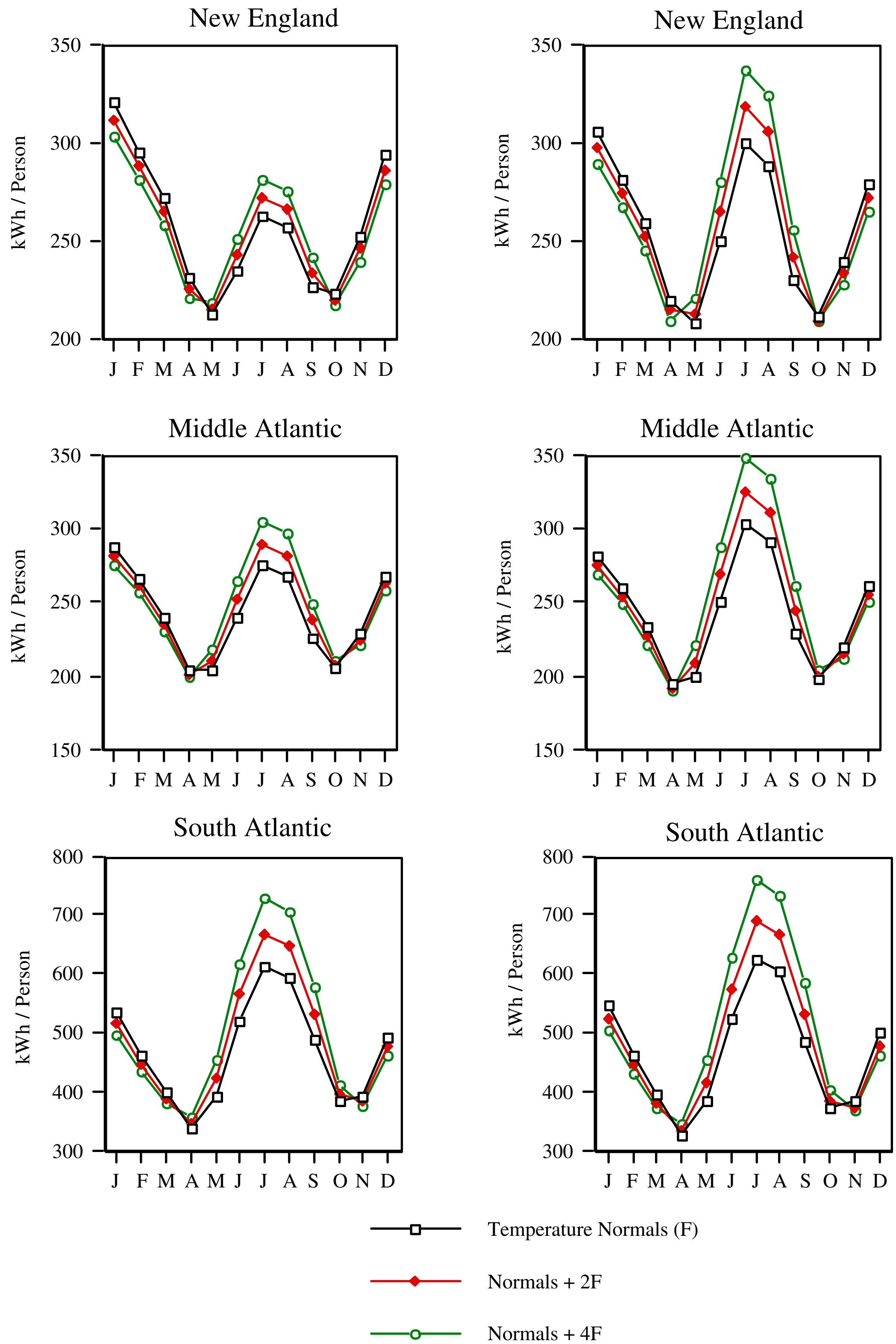
The figures presented in the subsequent sections entail both the census divisions' energy responses to climate scenarios based on the static degree-day statistical model (left column) and dynamic degree-days statistical model (right column). Appendix II contains the corresponding individual state energy demand responses to climate scenarios expressed as percent changes in energy demand (refer to Tables 50-59).

7.1.1 Residential Electricity Responses to Climate Scenarios

Residential electricity responses to climate scenarios are in Figure 37. In both the static and dynamic responses to the climate change scenarios electricity demand decreases during the heating season and increases during the cooling season relative to the temperature normals scenario in each of the census divisions. For New England, the static response to the +4°F scenario produces a 5.2% decrease in January electricity demand and a 7.1% increase in July relative to the temperature normals scenario. New England's corresponding dynamic response to the +4°F scenario indicates a 5.3% decrease in January electricity demand and a 12.6% increase in July electricity. In the Middle Atlantic, the +4°F scenario produces a 4.2% decrease in January electricity demand and a 10.8% increase in July electricity with the static response and a 4.7% decrease in January electricity demand and a 14.9% increase in July electricity dynamic response. Under the +4°F scenario the South Atlantic's residential electricity demand is projected with the static response to decrease 7.0% in January and increase 18.9% in July and with the dynamic response to decrease 8.1% in January and increase 21.1% in July. New England and the Middle Atlantic's projected increases in July electricity demand with the dynamic response is substantially higher than the static response because both of these regions exhibited increasing electricity demand sensitivity to cooling degree-days over the period of analysis (refer to section 6.2.1).

In response to the +4°F scenario, the static degree-day sensitivity models indicate annual electricity demand decreases 0.5% in New England, increases 2.4% in the Middle Atlantic, and increases 6.9% in the South Atlantic. The dynamic degree-day sensitivity models indicate annual electricity demand increases 2.0% in New England, increases 4.3% in the Middle Atlantic, and increases 7.6% in the South Atlantic. The net annual changes are, in absolute terms, substantially smaller than winter and summer months changes, which suggests that an analysis on an annual time-scale could significantly under appreciate the potential for increased peak loads and the concurrent need for additional peaking capacity.

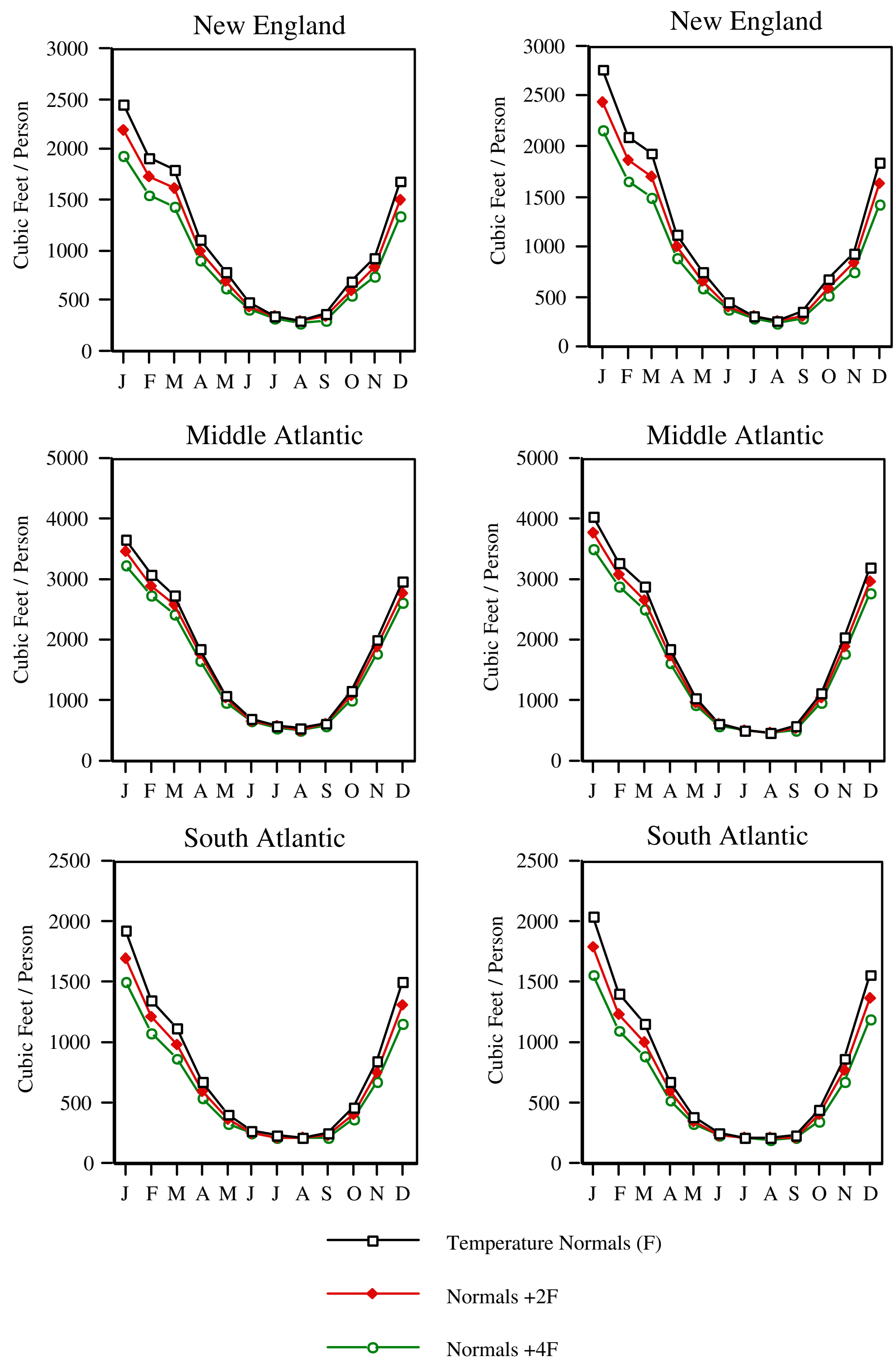
Figure 37. Census Divisions' Residential Electricity Demand Responses to Climate Scenarios with Static and Dynamic Degree-day Sensitivities.



7.1.2 Residential Natural Gas Responses to Climate Scenarios

Residential natural gas responses to climate scenarios are presented in Figure 38. The climate change scenarios produce significant decreases in natural gas demand with, for instance New England's annual demand decreasing 19.1%, the Middle Atlantic's demand decreasing 11%, and the South Atlantic's demand decreasing 20.2% in the +4°F climate scenario. The vast majority of these demand decreases occurs during the winter months. The differences in natural gas responses under the static and dynamic degree-day variables models is relatively small because natural gas sensitivity to heating degree-day has been relatively stable (refer to Table 33).

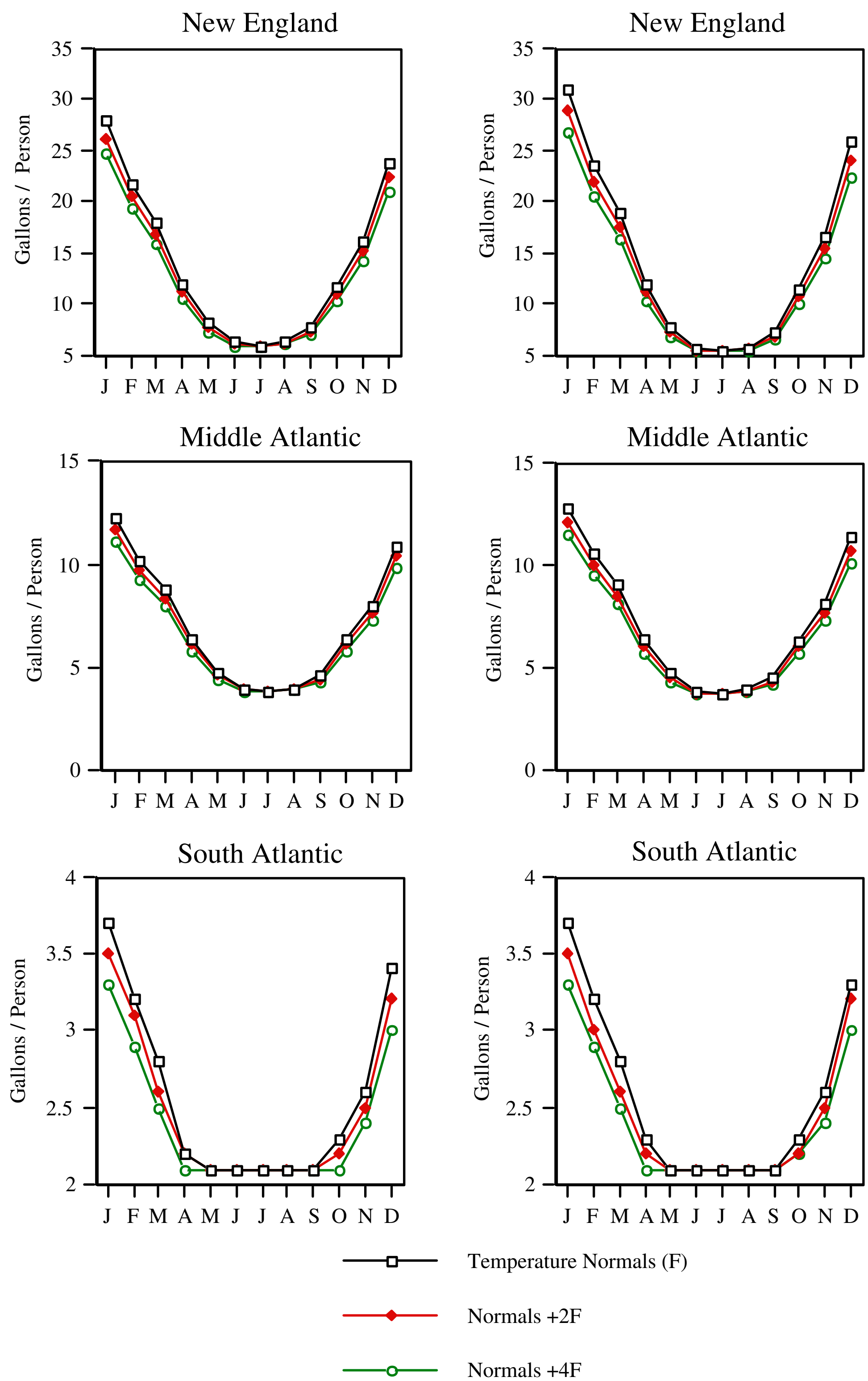
Figure 38. Census Divisions' Residential Natural Gas Demand Responses to Climate Scenarios with Static and Dynamic Degree-day Sensitivities.



7.1.3 Residential Heating Oil Responses to Climate Scenarios

Residential heating oil responses to climate scenarios are presented in Figure 39. Similar to the demand responses observed for natural gas, census division experience substantial decreases in heating oil demand in the climate change scenarios relative to the average temperature scenarios. Under the +4°F temperature scenario the static degree-day sensitivity results indicate annual heating oil demand declines 10.5% in New England, 8.2% in the Middle Atlantic, and 6% in the South Atlantic. The results of the dynamic degree-day sensitivity models are similar to the static models because no census division had a statistically significant change in heating oil demand sensitivity to degree-days over the period of analysis.

Figure 39. Census Divisions' Residential Heating Oil Demand Responses to Climate Scenarios with Static and Dynamic Degree-day Sensitivities.

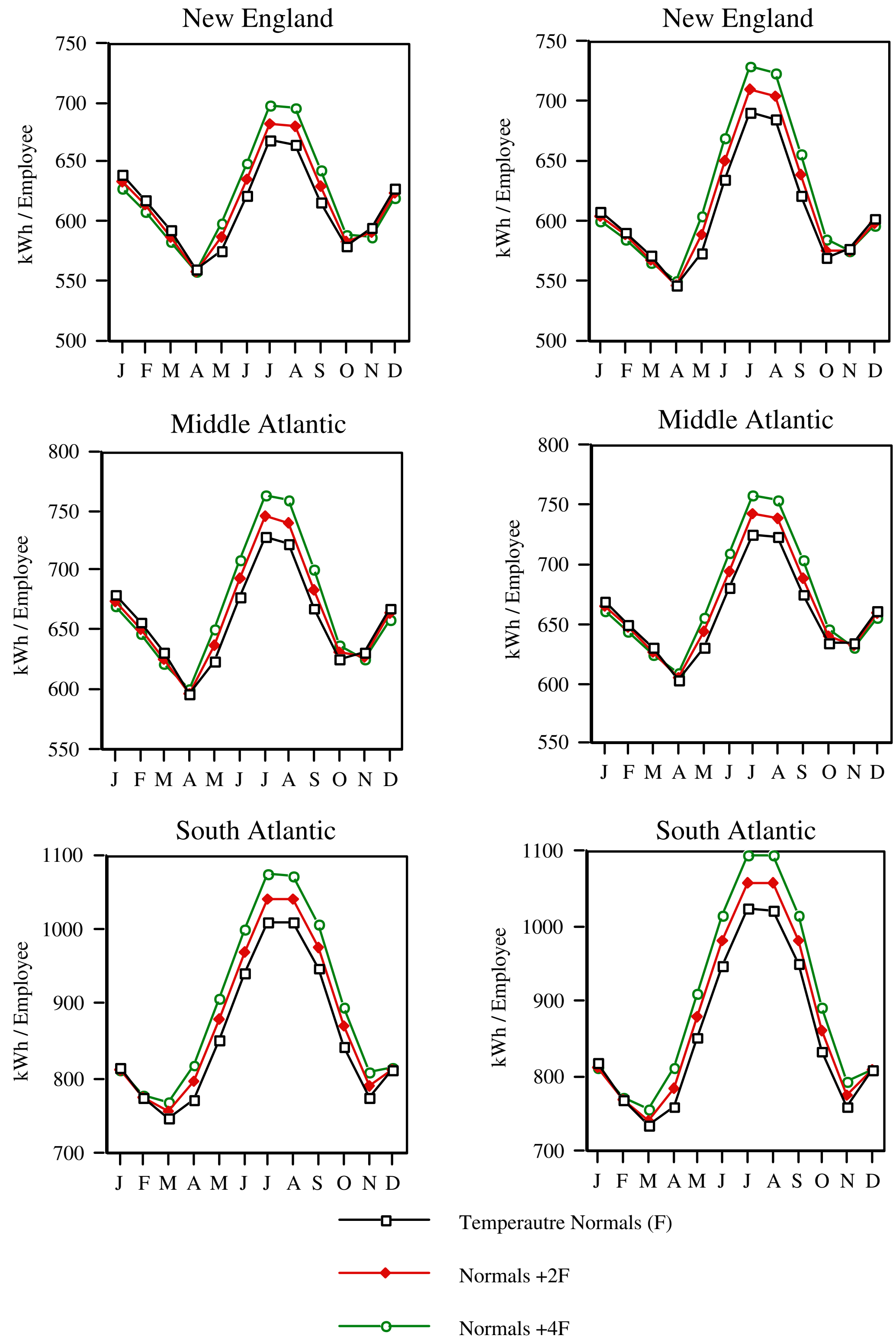


7.1.4 Commercial Electricity Responses to Climate Scenarios

Commercial electricity responses to climate scenarios are in Figure 40. Unlike the residential electricity responses, the commercial responses to climate scenarios produced by the static and dynamic degree-day sensitivity models are similar because commercial electricity demand sensitivity to degree-days has been relatively stable over the period of analysis.

In response to the +4°F warming scenario the static degree-day sensitivity models indicate a +1.4% change in annual electricity demand in New England, a +1.7% change in the Middle Atlantic, and a +4.5% change in the South Atlantic. The dynamic degree-day sensitivity models indicate a +2.3% change in annual electricity demand in New England, a +1.7% change in the Middle Atlantic, and a +4.9% change in the South Atlantic. Both the static and dynamic degree-day sensitivity models imply that in all the census divisions commercial electricity demands with climate change will increase more in the summers months than decrease in the winter months.

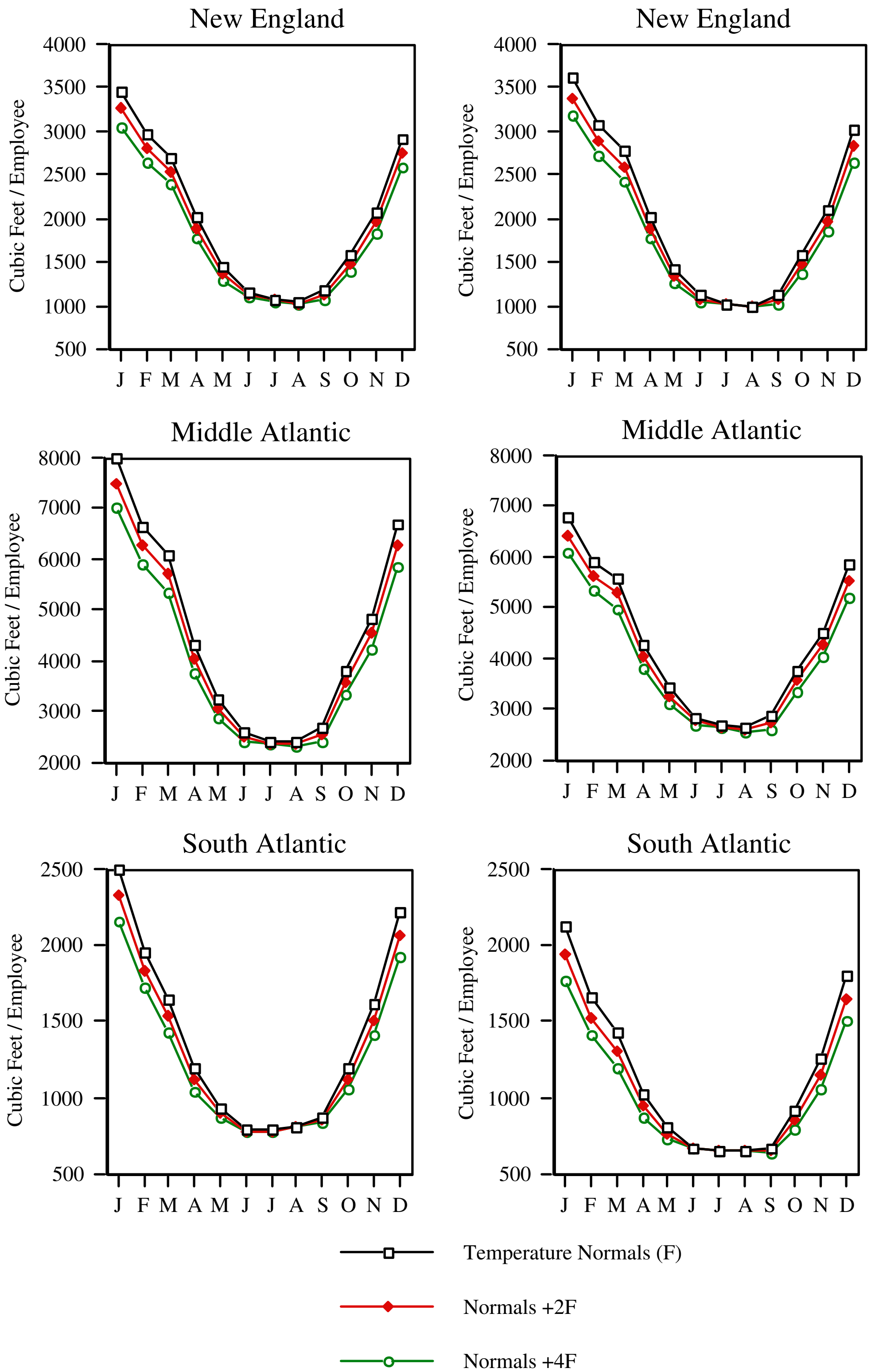
Figure 40. Census Divisions' Commercial Electricity Demand Responses to Climate Scenarios with Static and Dynamic Degree-day Sensitivities.



7.1.5 Commercial Natural Gas Responses to Climate Scenarios

Commercial natural gas responses to climate scenarios are presented in Figure 41. The climate change scenarios indicate a significant reduction in natural gas demand relative to the normals scenario. For instance under the +4°F climate scenario, New England's annual natural gas demand decreases 10.0%, the Middle Atlantic's demand decreases 11.0%, and the South Atlantic's demand decreases 10.2%. The Middle Atlantic's dynamic heating degree-day sensitivity variable indicates a decreasing sensitivity to heating degree-days, which results in a lower demand levels under the +4°F climate scenario relative to the static response.

Figure 41. Census Divisions' Commercial Natural Gas Demand Responses to Climate Scenarios with Static and Dynamic Degree-day Sensitivities.



7.2 Energy Demand Responses to Climate Scenarios With Adaptation

In this section, energy demand responses to climate scenarios are presented that include the effects of energy user adaptation to the climatic characteristics of the climate change scenario. The adaptive energy demand response models build on the models detailed in section 7.1 by endogenously specifying balance point temperature. The modification in balance point temperature to the temperature change of the climate change scenario is based on the results of the geographic analysis in section 6.3 as well as the observed historical balance point temperature. These models retain the energy demand sensitivities to 'hot' and 'cold' developed in section 6.2, but also incorporate adaptation by redefining 'hot' and 'cold'.

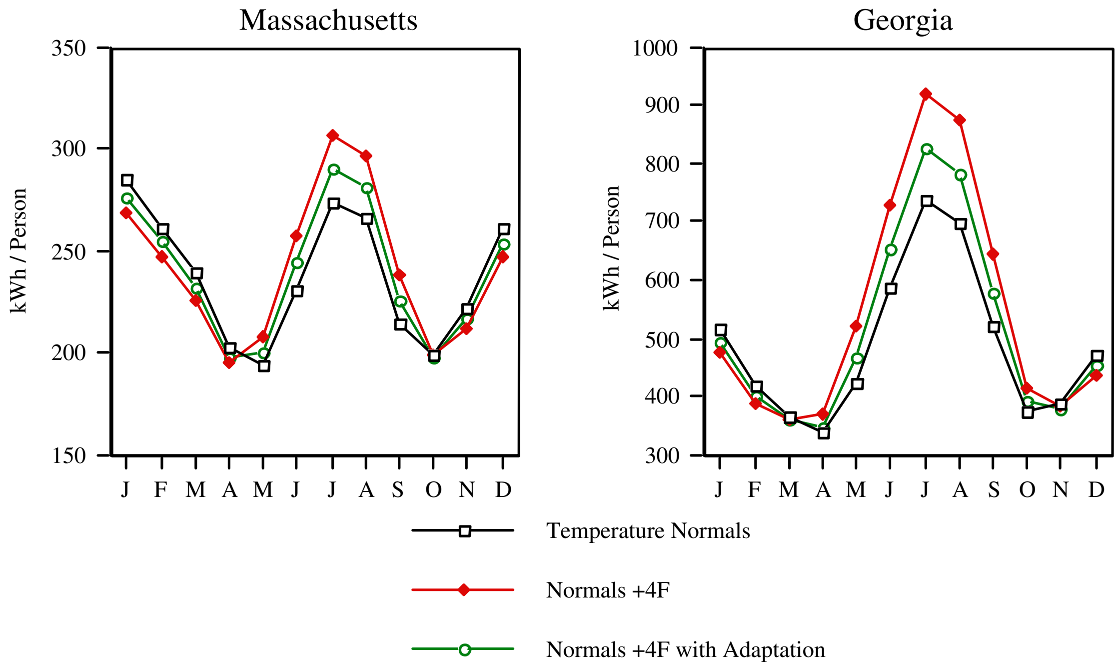
Adaptive energy demand responses to climate scenarios for Massachusetts and Georgia in the year 2005 are presented. To highlight the impact of adaptation on energy demand the figures include energy demand responses with and without adaptation to the same climate change scenario (+4°F). Three energy demand response scenarios are presented for each energy type and state. The first is the energy demand response to a climate scenario where monthly temperatures are the monthly 1971-2001 normals. The second is an energy demand response to a climate change scenario with no adaptation and average monthly temperatures are 4°F higher than the normals. The third scenario assumes adaptation and average monthly temperatures are 4°F higher than normal.

7.2.1 Residential Electricity Responses to Climate Scenarios

Residential electricity demand responses to climate and climate change scenarios for Massachusetts and Georgia are in Figure 42. In Massachusetts the balance point temperature shifts from 55°F to 57°F in the adaptation response with the 4°F temperature increase of the climate change scenario. Massachusetts' electricity demand responses to climate change with and without adaptation both indicate decreases in winter electricity demand and increases in summer electricity demands relative to the climate normals scenario. Moreover, winter demand reductions are larger under the non-adaptation response and, conversely, summer demand increases are smaller with the adaptation response relative to the climate normals scenario. Specifically, January's electricity demand decreases by 5.7% without adaptation and 3.0% with adaptation, whereas July's electricity demand increases by 11.7% without adaptation and 5.8% with adaptation. The net effect on annual electricity demand of a 4°F warming relative to the climate normals scenario is a 1.8% increase in demand in the non-adaptation response and a 0.7% increase in the adaptation response. Adaptation results in a small annual savings in electricity because the reduction in electricity demand during summer months is greater than the increase in electricity demand during the winter months.

Georgia's residential electricity demand responses to climate scenarios are in Figure 42. Similar to Massachusetts, both Georgia's non-adaptation and adaptation response to a +4°F warming indicate a decrease in winter electricity demand and an increase in summer demand. However, the reductions in winter demands are smaller and increases in summer demands are larger. To illustrate, January's decrease in electricity demand with the non-adaptation response is 4.2% while the decrease in the adaptation response is only 2.3%. The non-adaptation response indicates an electricity demand increase in July of 25.1%, whereas the adaptation response indicates July's demand increases by only 12.0%. The net affect of the non-adaptation response to the +4°F warming is an 11.5% increase in annual electricity demand relative to the temperature normals scenario. In contrast, with adaptation, in which the balance point shifts from 61°F to 63°F, annual electricity demand increases by only 5.2%. Adaptation results in significant energy savings in Georgia during the summer months relative to the marginal benefits during the winter months of non-adaptation. The findings indicate that adaptation more significantly reduces annual electricity demand in Georgia relative to Massachusetts. The decrease is larger in Georgia than in Massachusetts because (1) Georgia's electricity demand sensitivity to cooling degree-days is larger and (2) its current average temperature is higher than the balance point temperature such that the adapting balance point essentially catches back up to the increased temperature of the warming scenario.

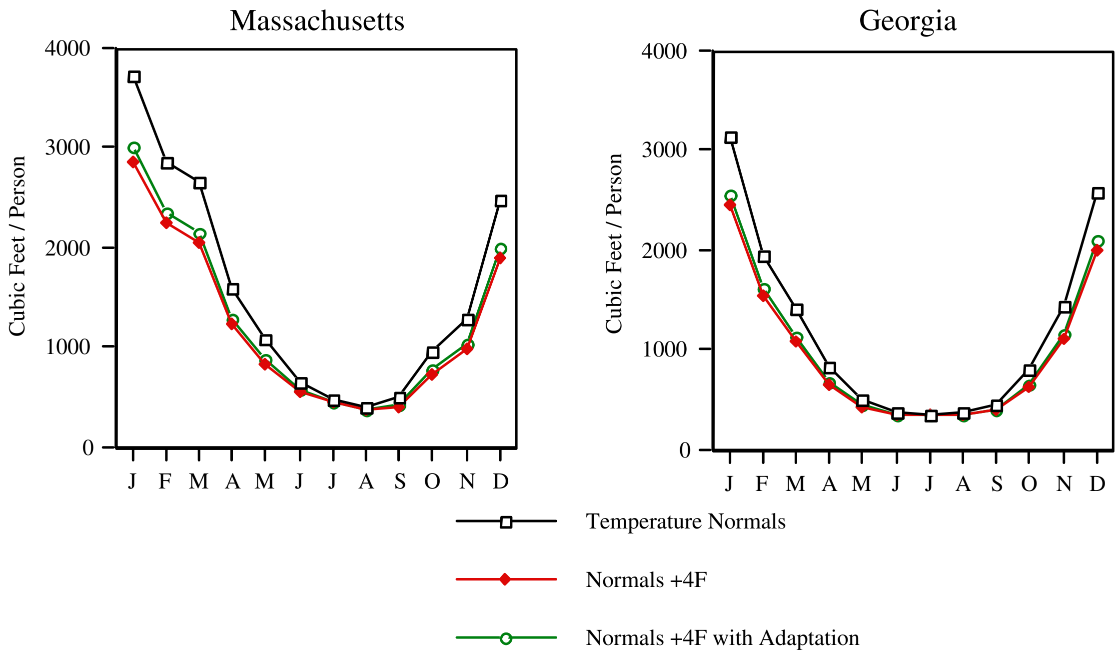
Figure 42. Residential Electricity Demand Responses to Climate Scenarios With and Without Adaptation in Massachusetts and Georgia.



7.2.2 Residential Natural Gas Responses to Climate Scenarios

The 4°F warming scenario produces significant reductions in Massachusetts and Georgia's residential natural gas demand in both the non-adaptation and adaptation responses (see Figure 43). Specifically, annual natural gas demand decreases in the non-adaptation response 21.5% in Massachusetts and 19.6% in Georgia. In the adaptation response natural gas demand decreases 18.0% in Massachusetts and 16.4% in Georgia. The similarity between non-adaptation and adaptation responses is due to the small climatic change-induced balance point temperature shift, an increase of 0.7°F with a 4°F warming. Somewhat counter-intuitively, adaptation results in higher demands for natural gas relative to the non-adaptation response. The relatively higher demands with adaptation to climate change is a result of the fact that society adapts to climate in order to reduce *overall* energy expenditures. The findings suggest that as temperature warms and heating services are required less often, the cost-effectiveness of certain technological adjustments, such as insulation levels, decrease. In effect, it becomes more cost-effective to use more energy and less capital. Additionally, because the price of cooling energy (i.e. electricity) is higher than heating energy the balance point temperature may be more biased towards decreasing cooling energy use.

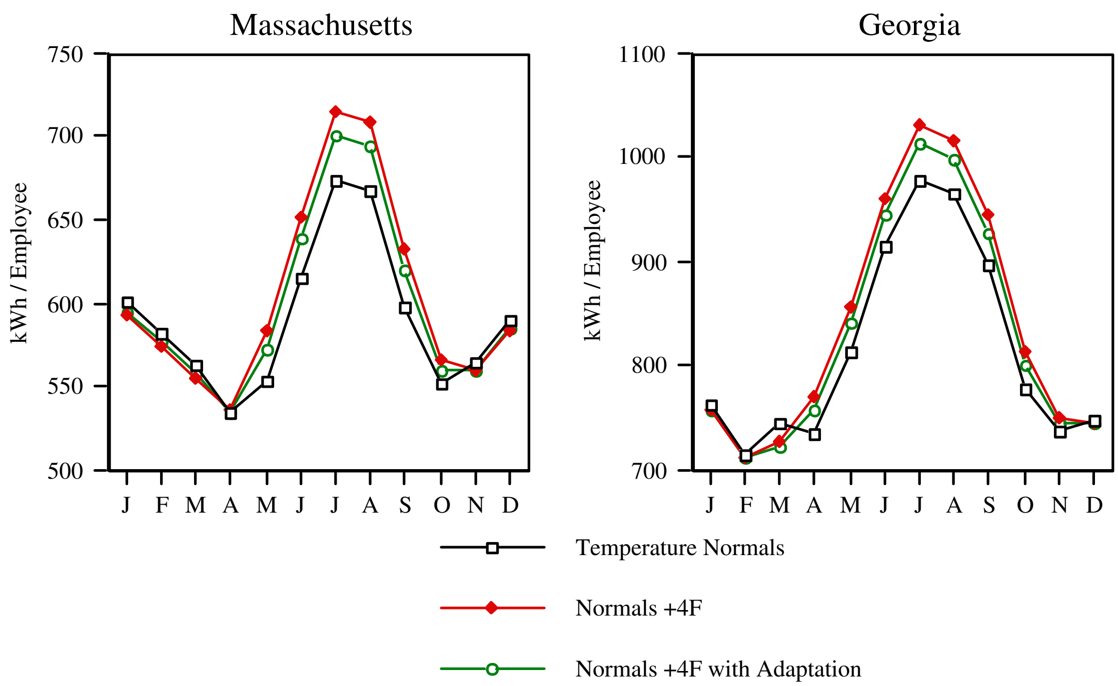
Figure 43. Residential Natural Gas Demand Responses to Climate Scenarios With and Without Adaptation in Massachusetts and Georgia.



7.2.3 Commercial Electricity Responses to Climate Scenarios

Massachusetts' and Georgia's commercial electricity demand responses to climate and climate change scenarios are in Figure 44. In both Massachusetts and Georgia the non-adaptation response and adaptation response indicate decreases in winter electricity demands and increases in summer electricity demands. Commercial adaptation responses more closely resemble the non-adaptation responses due to the smaller change in balance point temperature. With adaptation to the 4°F warming scenario, Massachusetts' commercial electricity balance point temperature shifts from 52°F to 53.3°F while Georgia's shifts from 54°F to 55.3°F. The net affects on annual commercial electricity demand in Massachusetts are a 2.3% increase with the non-adaptation response and a 1.5% increase with the adaptation response. In Georgia, annual commercial electricity demand increases 3.0% in non-adaptation case and 1.8% with adaptation.

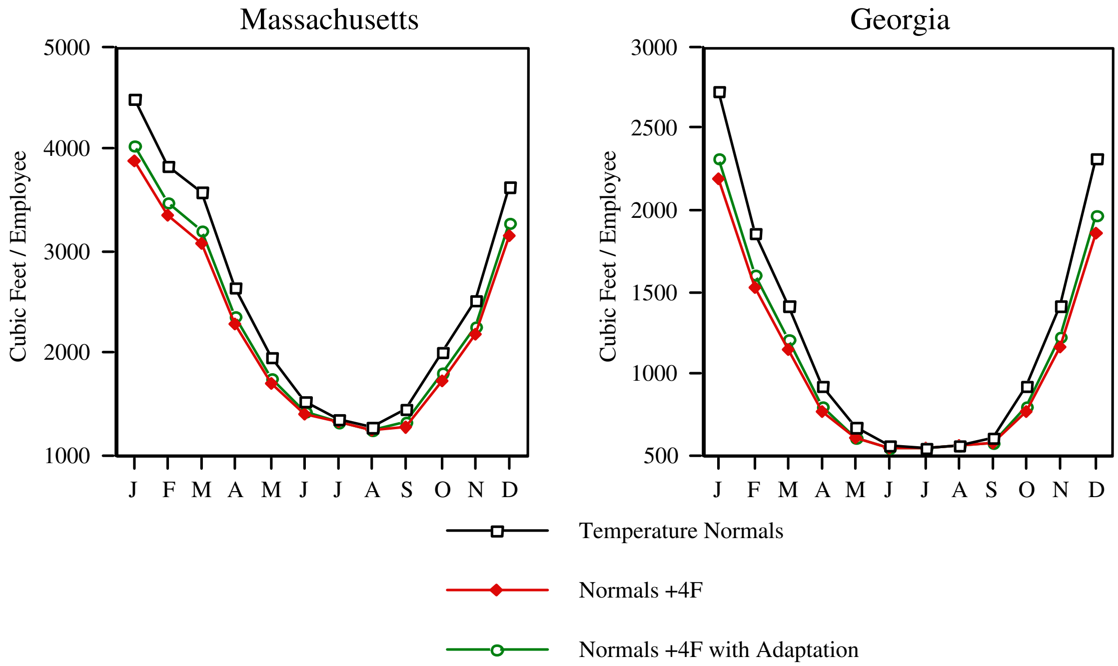
Figure 44. Commercial Electricity Demand Responses to Climate Scenarios With and Without Adaptation in Massachusetts and Georgia.



7.2.4 Commercial Natural Gas Responses to Climate Scenarios

Massachusetts and Georgia's commercial natural gas demand responses to climate and climate change scenarios are in Figure 45. The non-adaptation responses to the 4°F warming scenario indicate annual natural gas demand decreases 12.0% in Massachusetts and 15.5% in Georgia. In the adaptation response, natural gas demand decreases 9.2% in Massachusetts and 12.0% in Georgia. Compared to the residential natural gas responses, the commercial sector exhibits slightly larger differences between non-adaptation and adaptation responses due to the 1.0°F increase in balance point temperature with adaptation. Similar to the residential natural gas responses, adaptation results in relatively higher demands with the climate change scenario than with non-adaptation.

Figure 45. Commercial Natural Gas Demand Responses to Climate Scenarios With and Without Adaptation in Massachusetts and Georgia.



8. Concluding Chapter

8.1 Summary

This study explored potential impacts of climate change on energy demand utilizing the impact-adaptation assessment framework. Whereas previous studies analyzed the impacts of climate change based entirely on the historic sensitivity of energy demand, this project models impacts based on the sensitivity *and* adaptive capacity of energy demand to climatic variables. Accordingly, the research questions addressed in this dissertation were as follows:

- *Are energy demand sensitivities to temperature place-specific? If so, in what ways?*
- *Are adaptations by energy users to prevailing climate reflected in energy demand sensitivities to temperature? If so, in what ways?*

To answer these questions relating to sensitivity and adaptive capacity of energy demand, two separate methodologies were developed and applied due to their very different time responses to changes in temperature. The sensitivity of energy demand is an immediate, reactive response to temperature variability involving changes in utilization rates of current end-use technologies. Whereas adaptation of energy demand to climate is a long-term, reactive response involving changes in the attributes of energy-using capital or thermal attributes of buildings.

In answering the first research question, the study developed a temporal analysis methodology, which derived models of states' and census divisions' temperature-sensitive energy demands. Historic energy demand sensitivities to temperature variability were quantified, while controlling for energy prices, daylight hours, and changes in other socioeconomic factors. The results of the temporal analysis indicate significant variations in energy demand sensitivities between census divisions as well as between states. For instance, the sensitivity models developed in section 6.1.1 indicate that a 100 unit increase in cooling degree-days is associated with changes in monthly residential electricity from anywhere between +1.4% in Maine to +16.1% in Georgia. The spatial heterogeneity of energy demand sensitivities supports the hypothesis that impact assessments of energy demand should be performed at the regional level.

In addition to concluding that energy demand varies by region, this study discovered that, in general, energy demand sensitivities of states closely matched the sensitivities observed in their respective census division. This correlation is likely due to the similar climates of states in the same census division that, in turn, produce similar levels of adaptation to climate.

Having drawn a clear link between place and energy demand sensitivity, this dissertation employed a number of unique methodologies that assisted in better characterizing place-specific energy demand sensitivities to temperature. First, an iterative procedure was used to capture place-specific definitions of 'hot' and 'cold'. Consequently, the methodology provides a more accurate accounting of energy demand for cooling services and energy demand for heating services than assessments using 65°F to define 'hot' and 'cold'. Second, this dissertation created dynamic sensitivity variables to examine if and to what extent energy demand sensitivities to degree-days have changed over time. The findings demonstrate that accounting for such dynamics has significant implications for model results. In particular, residential electricity demand sensitivities to 'hot' temperatures increased in states in cooler climates, such as in New England. It thus seems probable that the increased sensitivities are a result of the increased use of air conditioners in housing units. Third, this analysis accounted for hours of daylight in each month such that estimates of monthly energy demand sensitivities to heating and cooling degree-days would not be biased because hours of daylight and temperature are correlated. In using these three new methodologies, this project clearly offers a better representation of energy demand sensitivities to degree-days than previous studies have presented.

In answering the second research question, a geographic analysis was used to discern adaptations by energy users to current climatic conditions, and to develop metrics to assess the likely adaptations to climate change. The results of the geographic analysis indicate a statistically significant association between climate and balance point temperatures for electricity and natural gas in the residential and commercial sectors. To illustrate, for every 1°F difference in average temperature between states a difference is expected in balance point temperature of 0.49°F for residential electricity, 0.18°F for residential natural gas, 0.34°F for commercial electricity, and 0.25°F for commercial natural gas. These findings suggest that energy users adapt to prevailing climate conditions by how they define and respond to 'hot' and 'cold'. If energy users reside in cooler climates, they reduce their energy use by defining 'cold' at a relatively lower temperature. The geographic analysis findings concluded that balance point temperatures vary with climate, which suggests that climate change may alter regional energy demand-temperature relations.

This study projected energy demand responses to climate change through three different assessment methods. The first projection method was based on the temporal analysis, which used the static degree-day sensitivities as detailed in section 7.1.1. The approach represents a business-as-usual scenario in which energy users continue to react to climate variability as if climate has not changed. In response to a 4°F warming scenario, the models projected changes in annual electricity demands ranging from -1.9% to +11.3% in the residential sector and +0.9% to +4.8% in the commercial sector. Intra-annual changes were more significant with most states' residential electricity demands increasing 10% to 20% during the summer months and commercial demands increasing 3% to 7% during such months. Projected annual changes in demands for natural gas and heating oil in response to a 4°F warming scenario were significantly larger then those for electricity because natural gas and heating oil are only demanded for heating services. Projected annual decreases in residential and commercial natural gas demands generally ranged from 10% to 20% whereas heating oil decreased 3% to 12%.

The second projection method was based on the temporal analysis, which used the dynamic degree-day sensitivities as detailed in section 7.1.2. The results closely matched the projections that used the static sensitivities except in the case of residential electricity. The findings indicate that electricity demands in regions with traditionally cooler climates may appreciate significantly in the future. For instance, electricity demand in Massachusetts was projected to increase by approximately 6% during the summer months with the static degree-day sensitivities, while it was projected to increase by 11% with the dynamic sensitivities.

The third projection method was based on a synthesis of the temporal and geographic analyses as detailed in section 7.2. These projections of energy demand responses include likely adaptations to climate change. In projecting energy demand responses to climate change scenarios in Massachusetts and Georgia, this study found that for both states adaptation results in lower electricity demands, but marginally higher natural gas demands relative to the non-adaptation projections. Specifically, Georgia's projected increases in residential demand for electricity were reduced with adaptation from 11.5% to 5.2% whereas projected decreases in residential natural gas demand were reduced with adaptation from 19.6% to 16.4%.

8.2 Methodological Lessons

This dissertation offers five methodological lessons that will be relevant to future impact assessments of climate change on energy demand. The first important methodological lesson of this study relates to how analyses of energy demand sensitivities to climate should be performed at the regional scale. Energy demand sensitivities are scale dependent because energy demand sensitivities differ in locales due to varying characteristics of energy supply infrastructure, energy-using capital, and energy users (Boustead, 1994). In part, these differences in energy demand sensitivities are due to adaptations to spatial variations in climate. To illustrate, this study observed significantly different perceptions of 'hot' and 'cold' as well as energy demand sensitivities to 'hot' and 'cold' between states. Accordingly, to present a comprehensive assessment of potential impacts of climate change, studies must account for the variations in energy use in a given region.

The second methodological lesson of this study is that if energy demand varies greatly within a year's period then the study should use a time-scale of less than one year in order to accurately account for variations in seasonal energy demand levels. In this study, monthly data was used to infer the seasonal effects of climate change on heating and cooling energy. The monthly models suggest significant intra-annual energy demand changes, which would not have been captured using annual data. This is particularly relevant for assessments of electricity demand because electricity cannot be stored and thus must be produced instantaneously during a given peak energy demand period.

The third methodological lesson is that energy demand analyses should dissaggregate by energy type (electricity, natural gas, heating oil) rather than examine aggregate energy demand. Due to the unique sensitivities and adaptive capacities of the various energy types, each will respond differently to climatic variables. Previous climate change studies that have focused on aggregate energy demand may have underestimated the energy impacts because the changes in cooling energy (electricity) and heating energy (natural gas and heating oil) were assumed to "offset" one another. In reality, however, this assumption overlooks the large capital costs associated with both the expansion of cooling energy services along with the contraction of heating energy services.

The fourth methodological lesson of this dissertation is that energy assessments need to consider the temporal dynamics of historic energy sensitivities. Unique to this analysis was the development of dynamic degree-day sensitivity variables to assess if and to what extent energy demand sensitivities have changed over time. The findings indicate that residential electricity sensitivities to cooling degree-days have markedly increased in cooler climates over the analysis period, likely a result of increased ownership and use of air-conditioners. Moreover, accounting for energy demand sensitivity dynamics is particularly relevant for assessments of global warming because air-conditioning market saturation rates appear to be correlated to ambient air temperature (Sailor and Pavlova, 2003).

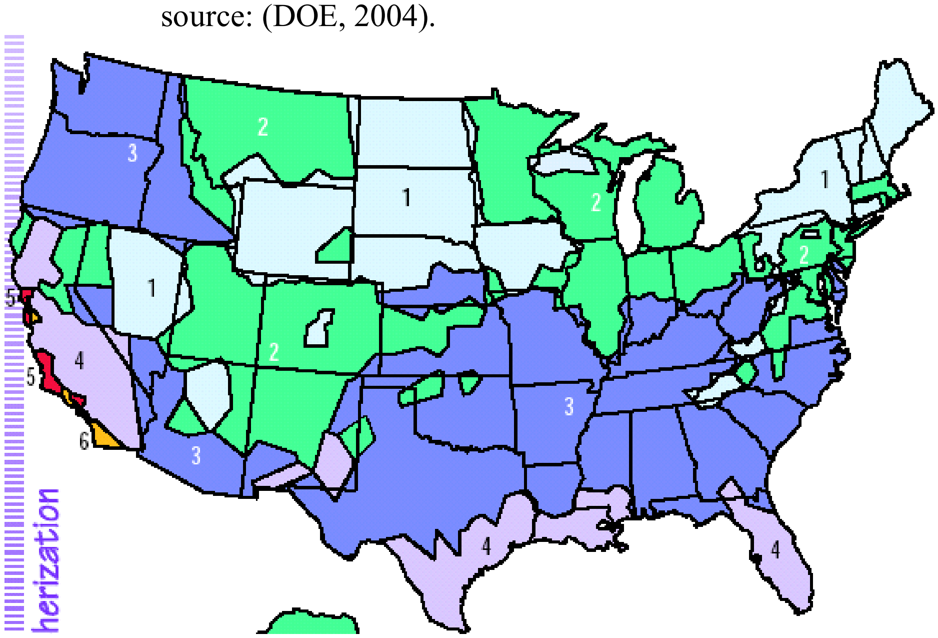
A fifth methodological lesson of this dissertation is that future energy assessments of climate change need to account for adaptation. This study was the first to account for adaptation levels to current climates and the first to consider the effects of adaptation in assessing energy demand responses to climate change. The project's results indicated significant adaptations by energy user to current climate, which suggests that with future climate change there will be new adaptations.

8.3 Avenues for Future Research

This dissertation offered new insights into regional sensitivities of energy demand to temperature, as well as new insights concerning adaptations of energy demand to variations in climate and the adaptive capacity of energy demand to climate change. The project specifically developed models of energy demand sensitivities in seventeen states, which were compared and quantitatively related to differences in adaptation levels to climate. Therefore, the study *implicitly* examined adaptations to climate through differences in the energy demand-temperature relation (V-shaped function). While the dissertation provided important conclusions and analyses relating to energy demand responses to climate change, it also raised additional questions that point to new avenues for future research.

One avenue for future research is to *explicitly* examine adaptations to climate. Whereas this study was a positive analysis that implicitly examined adaptations through differences in the energy demand-temperature relation (V-shaped function), future research could explicitly examine adaptations along with the effects of specific adaptation measures on the energy demand-temperature relationship. For instance, researchers could analyze changes in cost-effective levels of insulation, which are based on average weather conditions, in response to scenarios of climate change (see Figure 46). Consequently, future investigations could address such questions as: How would climate change spatially alter insulation zones? For a particular region, how would changes in insulation levels manifest themselves in the region's energy demand-temperature relation? By addressing such questions through an explicit examination of adaptations, future research could assist in prioritizing available public and private adaptation responses to climate change.

Figure 46. 'Insulation Zones' to Determine Cost-effective Insulation Levels, source: (DOE, 2004).



Another avenue for future research is to further explore the process of adaptation in the energy sector. In this study, adaptation to climate change was modeled based on differences in observed adaptation levels to current climates for regional energy systems at equilibrium. To model adaptations to climate change a better understanding of the dynamic between rates of climate change and the turnover rates of the building stock and temperature-sensitive energy using technologies is needed. Therefore, future research should attempt to create transient models portraying the dynamic relationship between capital stock attributes and climate change in order to determine the temporal malleability of the energy demand-temperature relation. Future investigations could address such questions as: When will adaptation to climate change occur? What will be the lag-time between changes in climate and changes in the V-shaped energy demand-temperature relation? Are adaptation policies available that could accelerate the process of adaptation? In taking such future research steps, researchers could better understand the process of adaptation and the appropriate timing of adaptation policies. The timing of adaptation policies is important for the energy sector, because adaptation options are less frequent in socioeconomic sectors that have slow rates of capital turnover and, thus, it may be critical to initiate new policies in the short term (Grubb et al., 1995; Fankhauser et al., 1999; Lempert, 2002).

The last avenue for future research relates to building designers and others involved in structuring the built environment as they might play a larger and more active role in human energy use policies and practices. As this study demonstrates, climatic conditions are a major determinant of energy demand and changes in climate will likely result in significant modifications of residential and commercial energy demands. Consequently, architects, building engineers, and standards organizations could play an important role in reducing building energy use. However, practitioners in these fields have thus far only superficially and in a qualitative manner examined the linkages between climate change, building energy performance, and building design (Millbanks, 1989; Taesler, 1990/91; Audin, 2001; Camilleri et al., 2001; Willis, 2001; Sanders and Phillipson, 2003; Shimoda, 2003). More research is needed to effectively calibrate the thermal envelopes of buildings and the sizing of space-conditioning technologies to new and changing climatic conditions. It is the responsibility of scholars, government officials, and members of the private sector alike to work together to formulate more useful and effective energy-saving technologies, building designs, and policies that account for ongoing climatic change.

Appendix I

Figure 47. Select Independent Variables in the Electricity Demand Models

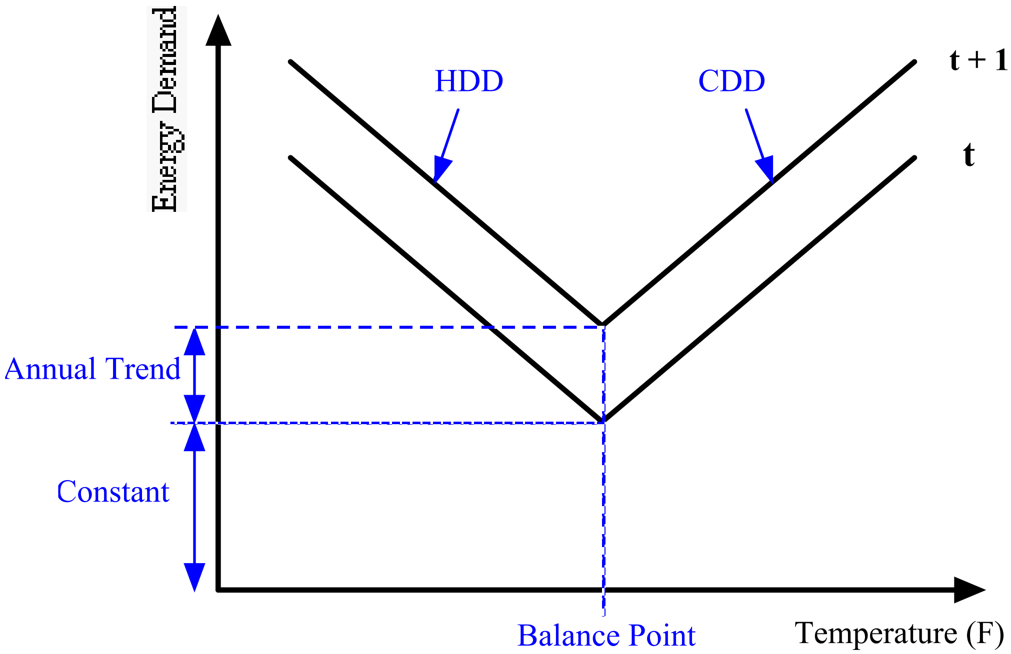
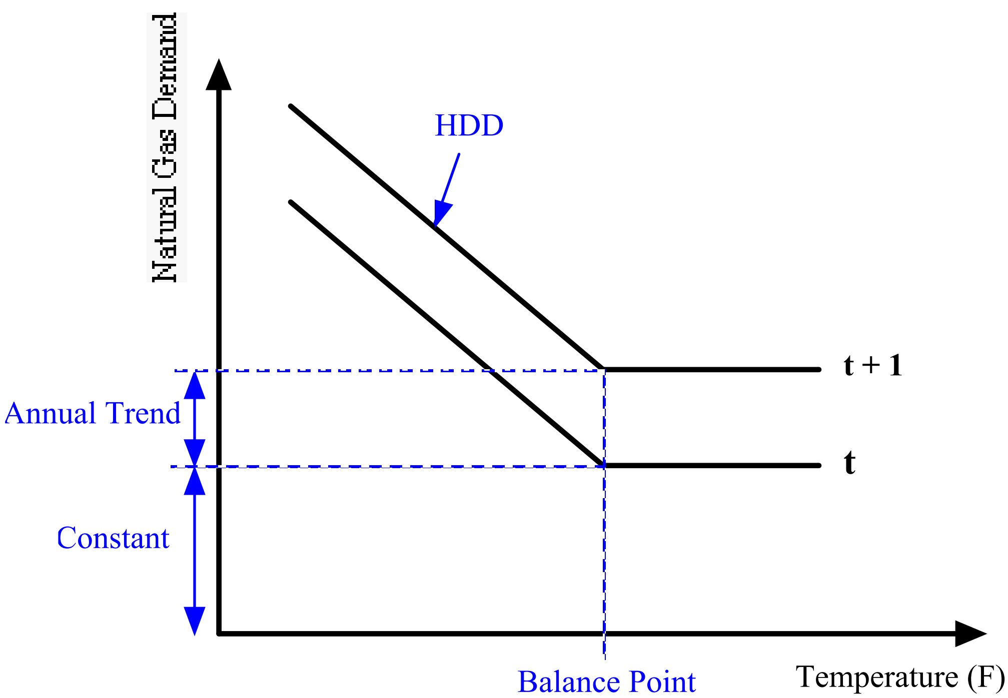


Figure 48. Select Independent Variables in the Natural Gas Demand Models



Appendix II

Table 50. Changes (%) in Residential Electricity with +4°F Temperature Scenario and Static Degree-day Sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	-1.9	-4.0	-3.6	-4.0	-3.7	-0.6	1.6	1.7	1.7	1.2	-2.8	-3.9	-4.0
NH	-1.4	-5.1	-4.6	-5.1	-4.3	0.9	4.9	5.1	5.1	3.8	-3.4	-4.9	-5.1
VT	-1.6	-4.6	-4.2	-4.6	-3.9	0.1	3.9	4.2	4.2	2.2	-3.4	-4.4	-4.6
MA	-0.5	-5.2	-4.7	-5.2	-4.0	3.1	6.0	6.3	6.3	5.8	-1.0	-4.5	-5.1
CT	0.4	-6.3	-5.8	-6.3	-4.6	5.0	10.0	10.4	10.4	9.5	-1.0	-5.7	-6.2
RI	0.8	-4.5	-4.1	-4.5	-3.1	4.5	7.2	7.5	7.5	7.1	1.1	-3.5	-4.1
NY	2.1	-2.7	-2.5	-2.5	0.3	6.0	7.0	7.2	7.2	7.0	2.4	-1.9	-2.4
NJ	5.6	-4.7	-4.3	-4.4	-1.0	12.3	16.0	16.6	16.6	15.9	4.1	-3.6	-4.4
PA	1.0	-6.0	-5.4	-5.9	-4.6	4.1	12.0	13.0	13.0	10.1	-2.0	-5.6	-6.0
DE	2.0	-6.5	-5.8	-6.1	0.6	9.5	10.4	10.8	10.8	10.4	2.9	-4.4	-6.6
MD	2.0	-8.7	-7.8	-8.2	-3.4	9.6	14.9	15.5	15.5	14.3	0.7	-7.2	-8.5
VA	1.7	-10.9	-9.9	-10.4	-3.8	10.1	17.8	18.6	18.6	16.7	-0.2	-9.2	-10.3
WV	-0.7	-8.7	-8.0	-8.3	-6.5	2.6	12.7	14.5	14.4	9.9	-4.2	-7.9	-8.7
NC	2.8	-8.5	-7.9	-7.2	1.4	12.1	14.0	14.5	14.5	13.9	1.9	-5.9	-8.4
SC	4.2	-7.0	-6.8	-5.4	2.2	12.5	14.0	14.6	14.6	14.0	2.8	-4.6	-7.1
GA	9.9	-7.1	-6.9	-1.4	8.4	20.2	21.3	22.0	22.0	21.3	9.3	-0.8	-7.1
FL	11.3	0.7	1.7	5.1	12.5	16.6	16.1	16.6	16.6	16.1	16.0	7.4	2.2

Table 51. Changes (%) in Residential Electricity with +4°F Temperature Scenario and Dynamic Degree-day Sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	0.0	-2.9	-2.6	-2.9	-2.6	1.4	4.3	4.5	4.5	3.7	-1.4	-2.7	-2.8
NH	1.3	-6.0	-5.4	-6.0	-4.8	5.0	12.7	13.3	13.3	10.6	-3.0	-5.8	-6.0
VT	0.7	-3.8	-3.5	-3.8	-2.9	2.8	8.0	8.6	8.6	5.6	-2.1	-3.6	-3.7
MA	1.8	-5.7	-5.2	-5.7	-4.0	6.8	11.3	11.7	11.7	10.9	0.6	-4.9	-5.5
CT	2.9	-7.4	-6.8	-7.4	-5.2	9.0	16.5	17.2	17.2	15.8	0.2	-6.7	-7.3
RI	3.6	-3.0	-2.7	-3.0	-1.5	7.5	10.6	10.9	10.9	10.5	3.5	-1.9	-2.6
NY	3.2	-3.6	-3.3	-3.4	0.5	8.5	9.9	10.2	10.2	9.9	3.5	-2.4	-3.2
NJ	7.6	-4.5	-4.0	-4.1	-0.3	14.6	18.8	19.5	19.5	18.8	5.4	-3.2	-4.1
PA	4.0	-6.2	-5.6	-6.0	-4.5	7.5	18.5	20.1	20.0	15.9	-0.9	-5.7	-6.2
DE	2.7	-6.8	-6.1	-6.4	1.0	10.9	11.9	12.3	12.3	11.9	3.6	-4.5	-6.9
MD	3.1	-9.8	-8.9	-9.3	-3.6	11.9	18.4	19.2	19.2	17.7	1.2	-8.1	-9.7
VA	3.9	-11.2	-10.1	-10.6	-3.1	12.9	22.0	22.9	22.9	20.6	1.0	-9.3	-10.5
WV	0.9	-9.6	-8.8	-9.1	-6.8	4.8	17.8	20.2	20.1	14.2	-3.9	-8.6	-9.6
NC	4.2	-9.0	-8.4	-7.5	2.3	14.6	16.7	17.3	17.3	16.6	2.8	-6.1	-8.8
SC	4.9	-7.3	-7.1	-5.7	2.6	13.7	15.4	16.0	16.0	15.4	3.2	-4.8	-7.4
GA	11.5	-8.1	-7.9	-1.7	9.4	22.9	24.2	25.1	25.1	24.2	10.4	-1.0	-8.1
FL	10.8	-2.6	-1.0	2.9	12.6	17.6	17.1	17.8	17.8	17.1	16.9	6.0	-0.8

Table 52. Changes (%) in Residential Natural Gas with +4°F Temperature Scenario and Static Degree-day Sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	-13.5	-14.0	-12.7	-14.0	-13.5	-14.0	-13.1	-10.2	-11.8	-13.5	-14.0	-13.5	-14.0
NH	-20.1	-20.7	-18.9	-20.7	-20.1	-20.7	-19.4	-16.0	-18.6	-20.1	-20.7	-20.1	-20.7
VT	-10.0	-10.5	-9.6	-10.5	-10.2	-10.0	-8.2	-5.0	-6.3	-10.0	-10.5	-10.2	-10.5
MA	-20.7	-21.9	-20.0	-21.9	-21.3	-21.9	-16.6	-8.4	-10.8	-20.5	-21.9	-21.3	-21.9
CT	-18.8	-20.2	-18.4	-20.2	-19.6	-19.4	-13.4	-5.6	-7.8	-18.1	-20.2	-19.6	-20.2
RI	-16.8	-17.9	-16.3	-17.9	-17.4	-17.9	-13.8	-6.3	-7.6	-15.8	-17.9	-17.4	-17.9
NY	-14.7	-15.7	-14.3	-15.7	-15.3	-15.0	-11.1	-5.6	-7.3	-14.4	-15.7	-15.3	-15.7
NJ	-14.0	-15.5	-14.1	-15.5	-15.0	-14.2	-6.9	-1.3	-2.7	-11.4	-15.0	-15.0	-15.5
PA	-10.9	-11.9	-10.8	-11.9	-11.6	-10.4	-5.4	-1.5	-2.9	-8.9	-11.5	-11.6	-11.9
DE	-10.6	-11.8	-10.7	-11.8	-11.5	-10.6	-4.8	-0.9	-1.8	-7.9	-11.3	-11.5	-11.8
MD	-9.7	-10.9	-9.9	-10.9	-10.6	-9.2	-3.8	-0.9	-1.6	-6.6	-10.4	-10.6	-10.9
VA	-19.4	-21.4	-19.5	-21.4	-20.8	-18.1	-7.5	-1.5	-3.1	-12.7	-20.2	-20.8	-21.4
WV	-13.4	-14.4	-13.1	-14.4	-13.9	-12.8	-7.9	-4.2	-6.1	-11.7	-14.4	-13.9	-14.4
NC	-13.2	-14.7	-13.4	-14.7	-13.9	-10.5	-3.4	-0.5	-1.0	-7.3	-13.7	-14.3	-14.7
SC	-18.4	-20.2	-18.4	-20.2	-19.6	-15.9	-7.2	-1.8	-2.9	-11.8	-18.7	-19.6	-20.2
GA	-18.7	-21.5	-19.6	-21.5	-19.8	-13.6	-4.0	-1.0	-1.0	-9.3	-19.6	-20.9	-21.5
FL	-3.2	-4.7	-4.4	-4.5	-3.5	-1.5	-0.1	0.0	0.0	0.0	-2.4	-4.0	-4.8

Table 53. Changes (%) in Residential Natural Gas with +4°F Temperature Scenario and Dynamic Degree-day Sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	-15.9	-16.4	-14.9	-16.4	-15.9	-16.4	-15.4	-12.0	-13.9	-15.9	-16.4	-15.9	-16.4
NH	-22.0	-22.6	-20.7	-22.6	-22.0	-22.6	-21.1	-17.5	-20.3	-22.0	-22.6	-22.0	-22.6
VT	-10.7	-11.3	-10.3	-11.3	-11.0	-10.8	-8.8	-5.4	-6.8	-10.7	-11.3	-11.0	-11.3
MA	-21.9	-23.2	-21.2	-23.2	-22.5	-23.2	-17.6	-8.9	-11.4	-21.7	-23.2	-22.5	-23.2
CT	-22.6	-23.8	-21.8	-23.8	-23.1	-23.0	-15.9	-6.8	-9.4	-21.4	-23.8	-23.1	-23.8
RI	-17.8	-18.9	-17.2	-18.9	-18.3	-18.9	-14.5	-6.7	-8.1	-16.7	-18.9	-18.3	-18.9
NY	-15.4	-16.4	-15.0	-16.4	-15.9	-15.7	-11.6	-5.9	-7.6	-15.1	-16.4	-15.9	-16.4
NJ	-18.4	-19.9	-18.2	-19.9	-19.3	-18.3	-9.0	-1.8	-3.5	-14.7	-19.3	-19.3	-19.9
PA	-12.0	-13.1	-11.9	-13.1	-12.7	-11.4	-5.9	-1.7	-3.2	-9.8	-12.6	-12.7	-13.1
DE	-12.2	-13.5	-12.2	-13.5	-13.1	-12.1	-5.4	-1.0	-2.1	-9.0	-12.9	-13.1	-13.5
MD	-10.7	-12.0	-10.9	-12.0	-11.6	-10.1	-4.2	-1.0	-1.7	-7.2	-11.4	-11.6	-12.0
VA	-21.6	-23.5	-21.5	-23.5	-22.8	-20.0	-8.3	-1.7	-3.4	-14.0	-22.2	-22.8	-23.5
WV	-14.5	-15.4	-14.1	-15.4	-15.0	-13.8	-8.5	-4.5	-6.5	-12.7	-15.4	-15.0	-15.4
NC	-13.2	-14.7	-13.4	-14.7	-13.8	-10.5	-3.4	-0.5	-1.0	-7.3	-13.7	-14.3	-14.7
SC	-17.3	-19.1	-17.5	-19.1	-18.6	-15.0	-6.8	-1.7	-2.7	-11.2	-17.7	-18.6	-19.1
GA	-19.6	-22.4	-20.4	-22.4	-20.6	-14.2	-4.2	-1.0	-1.0	-9.7	-20.4	-21.7	-22.4
FL	-1.6	-2.5	-2.3	-2.4	-1.8	-0.8	0.0	0.0	0.0	0.0	-1.2	-2.1	-2.5

Table 54. Changes (%) in Residential Heating Oil with +4°F Temperature Scenario with Static Degree-day Sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	-8.1	-8.3	-7.5	-8.3	-8.1	-8.3	-8.1	-7.3	-7.7	-8.1	-8.3	-8.1	-8.3
NH	-8.8	-9.1	-8.3	-9.1	-8.8	-9.1	-8.6	-7.5	-8.4	-8.8	-9.1	-8.8	-9.1
VT	-8.9	-9.2	-8.3	-9.2	-8.9	-9.2	-8.6	-7.5	-8.2	-8.9	-9.2	-8.9	-9.2
MA	-12.2	-13.4	-12.1	-13.4	-13.0	-13.1	-8.1	-2.6	-4.1	-11.6	-13.4	-13.0	-13.4
CT	-11.9	-14.3	-13.0	-14.3	-13.9	-9.4	-1.5	-0.1	-0.2	-5.3	-13.3	-13.9	-14.3
RI	-11.1	-12.8	-11.7	-12.8	-12.4	-11.8	-5.2	-0.6	-0.9	-7.2	-12.2	-12.4	-12.8
NY	-10.1	-11.8	-10.7	-11.8	-11.4	-10.2	-4.3	-0.7	-1.0	-7.3	-11.2	-11.4	-11.8
NJ	-8.4	-11.1	-10.0	-11.1	-10.4	-6.0	-0.6	0.0	-0.1	-2.0	-9.5	-10.7	-11.1
PA	-5.8	-9.4	-8.5	-8.7	-6.5	-1.8	-0.1	0.0	0.0	-0.2	-5.1	-8.4	-8.8
DE	-8.8	-13.1	-11.8	-13.0	-9.1	-1.6	0.0	0.0	0.0	0.0	-7.0	-12.0	-12.9
MD	-10.4	-13.6	-12.4	-13.6	-12.1	-6.6	-0.4	-0.1	-0.1	-1.8	-10.9	-13.2	-13.6
VA	-6.3	-9.1	-8.2	-9.1	-8.2	-4.5	-0.4	-0.1	-0.1	-1.6	-7.4	-8.5	-9.1
WV	1.0	1.2	1.1	1.2	1.2	1.1	0.7	0.4	0.6	1.1	1.2	1.2	1.2
NC	-4.6	-8.3	-7.7	-7.9	-4.5	-0.8	0.0	0.0	0.0	-0.1	-4.5	-7.3	-8.2
SC	-3.7	-9.2	-7.8	-5.5	-0.6	-0.1	0.0	0.0	0.0	0.0	-1.1	-5.4	-8.7
GA	-2.3	-3.9	-3.5	-3.7	-3.3	-1.8	-0.2	-0.1	0.0	-0.7	-3.1	-3.5	-3.9
FL	-3.0	-5.0	-4.5	-4.9	-4.3	-2.5	-0.4	0.0	0.0	-0.2	-3.1	-4.6	-5.0

Table 55. Changes (%) in Residential Heating Oil with +4°F Temperature Scenario and Dynamic degree-day sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	-8.9	-9.2	-8.3	-9.2	-8.9	-9.2	-8.9	-8.0	-8.5	-8.9	-9.2	-8.9	-9.2
NH	-12.7	-13.1	-11.9	-13.1	-12.7	-13.1	-12.4	-10.9	-12.1	-12.7	-13.1	-12.7	-13.1
VT	-11.7	-12.1	-11.0	-12.1	-11.7	-12.1	-11.3	-9.9	-10.9	-11.7	-12.1	-11.7	-12.1
MA	-13.9	-15.1	-13.7	-15.1	-14.6	-14.7	-9.2	-3.0	-4.6	-13.2	-15.1	-14.6	-15.1
CT	-14.0	-16.5	-15.1	-16.5	-16.0	-10.9	-1.7	-0.1	-0.3	-6.2	-15.4	-16.0	-16.5
RI	-12.8	-14.6	-13.3	-14.6	-14.1	-13.5	-5.9	-0.6	-1.0	-8.3	-13.9	-14.1	-14.6
NY	-10.8	-12.6	-11.4	-12.6	-12.2	-10.8	-4.6	-0.8	-1.1	-7.8	-12.0	-12.2	-12.6
NJ	-9.7	-12.5	-11.3	-12.5	-11.7	-6.8	-0.6	0.0	-0.1	-2.2	-10.8	-12.1	-12.5
PA	-7.0	-11.0	-10.0	-10.2	-7.7	-2.1	-0.1	0.0	0.0	-0.2	-6.0	-9.9	-10.3
DE	-8.1	-12.1	-11.0	-12.1	-8.4	-1.5	0.0	0.0	0.0	0.0	-6.5	-11.2	-12.0
MD	-12.4	-15.8	-14.4	-15.8	-14.0	-7.7	-0.4	-0.1	-0.1	-2.1	-12.7	-15.3	-15.8
VA	-5.7	-8.4	-7.6	-8.4	-7.5	-4.1	-0.4	-0.1	-0.1	-1.5	-6.8	-7.8	-8.4
WV	2.0	2.4	2.1	2.4	2.3	2.2	1.4	0.8	1.1	2.0	2.4	2.3	2.4
NC	-4.4	-8.0	-7.4	-7.6	-4.3	-0.8	0.0	0.0	0.0	-0.1	-4.3	-7.0	-7.9
SC	-3.7	-9.3	-7.9	-5.6	-0.6	-0.1	0.0	0.0	0.0	0.0	-1.1	-5.5	-8.9
GA	-2.0	-3.5	-3.1	-3.3	-3.0	-1.6	-0.2	-0.1	0.0	-0.6	-2.8	-3.1	-3.5
FL	-1.3	-2.3	-2.1	-2.3	-2.0	-1.2	-0.2	0.0	0.0	-0.1	-1.4	-2.1	-2.3

Table 56. Changes (%) in Commercial Electricity with +4°F Temperature Scenario and Static Degree-day Sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	0.9	-1.4	-1.3	-1.3	0.2	3.0	3.1	3.2	3.2	3.1	1.5	-0.9	-1.2
NH	0.8	-2.5	-2.2	-2.1	0.6	3.4	3.5	3.6	3.6	3.5	1.7	-1.3	-2.1
VT	0.9	-1.3	-1.2	-1.2	-0.2	2.6	3.4	3.5	3.5	3.2	0.6	-1.1	-1.1
MA	1.5	-1.6	-1.4	-1.5	0.0	4.1	4.5	4.7	4.7	4.5	1.6	-1.0	-1.4
CT	1.5	-1.5	-1.4	-1.3	1.1	3.9	4.0	4.2	4.2	4.0	2.2	-0.5	-1.4
RI	2.1	-1.0	-0.9	-0.9	1.4	4.5	4.6	4.7	4.7	4.6	3.3	0.6	-0.7
NY	2.1	-0.9	-0.8	-0.7	1.2	4.5	4.8	5.0	5.0	4.8	2.4	-0.2	-0.7
NJ	2.5	-1.0	-0.9	-0.9	0.8	5.3	6.1	6.3	6.3	6.0	2.4	-0.6	-0.9
PA	1.0	-1.8	-1.6	-1.5	-0.1	3.0	4.0	4.2	4.2	4.0	0.9	-1.4	-1.6
DE	2.0	-2.1	-1.8	-1.4	2.0	5.0	5.0	5.2	5.2	5.0	3.2	-0.1	-1.8
MD	2.4	-2.7	-2.4	-1.8	2.4	5.9	6.0	6.2	6.2	6.0	3.4	-0.6	-2.4
VA	2.7	-2.5	-2.3	-1.7	2.6	6.5	6.7	6.9	6.9	6.7	3.0	-0.6	-2.3
WV	1.1	-3.4	-3.1	-2.4	1.0	4.3	5.0	5.2	5.2	5.0	1.2	-1.8	-3.2
NC	3.6	-1.0	-0.5	1.7	5.2	5.8	5.6	5.8	5.8	5.6	5.2	2.0	-0.3
SC	4.8	-0.4	-0.1	2.6	6.3	7.6	7.3	7.6	7.6	7.3	6.0	2.6	-0.1
GA	2.9	-1.6	-0.9	-2.7	4.8	5.5	5.3	5.5	5.5	5.3	4.7	1.4	-1.0
FL	4.7	2.4	3.5	4.8	5.0	5.2	5.0	5.2	5.2	5.0	5.2	5.0	4.1

Table 57. Changes (%) in Commercial Electricity with +4°F Temperature Scenario and Dynamic Degree-day Sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	1.5	-0.5	-0.4	-0.4	0.8	3.2	3.3	3.4	3.4	3.3	1.9	-0.1	-0.3
NH	1.4	-3.1	-2.8	-2.6	1.1	4.9	4.9	5.1	5.1	4.9	2.6	-1.5	-2.6
VT	2.1	-0.3	-0.3	-0.3	0.8	3.8	4.6	4.8	4.8	4.4	1.7	-0.2	-0.2
MA	2.3	-1.4	-1.3	-1.3	0.4	5.4	5.9	6.1	6.1	5.9	2.4	-0.7	-1.2
CT	2.0	-0.7	-0.7	-0.5	1.6	4.1	4.2	4.3	4.3	4.2	2.6	0.2	-0.6
RI	3.4	0.1	0.1	0.2	2.5	5.7	5.8	6.0	6.0	5.8	4.5	1.8	0.5
NY	1.8	-0.7	-0.6	-0.6	1.1	3.8	4.1	4.3	4.3	4.1	2.1	-0.2	-0.5
NJ	3.0	0.1	0.1	0.2	1.5	5.2	5.7	5.9	5.9	5.7	2.8	0.4	0.2
PA	1.5	-1.7	-1.5	-1.4	0.1	3.6	4.7	4.9	4.9	4.7	1.3	-1.2	-1.5
DE	2.0	-2.5	-2.2	-1.7	2.0	5.3	5.3	5.4	5.4	5.3	3.3	-0.3	-2.2
MD	3.0	-1.7	-1.5	-0.8	3.0	6.1	6.2	6.4	6.4	6.2	3.9	0.3	-1.4
VA	3.1	-1.7	-1.6	-1.0	3.0	6.4	6.6	6.9	6.9	6.6	3.3	0.0	-1.5
WV	1.7	-3.6	-3.2	-2.4	1.5	5.4	6.2	6.4	6.4	6.2	1.8	-1.8	-3.3
NC	4.0	-1.3	-0.6	1.9	5.9	6.6	6.4	6.6	6.6	6.4	5.8	2.1	-0.4
SC	5.1	-1.1	-0.8	2.4	6.9	8.4	8.1	8.4	8.4	8.1	6.6	2.4	-0.8
GA	3.0	-0.9	-0.3	-2.3	4.6	5.3	5.1	5.3	5.3	5.1	4.6	1.7	-0.4
FL	4.7	0.1	2.8	5.0	5.4	5.6	5.4	5.6	5.6	5.4	5.6	5.3	3.4

Table 58. Changes (%) in Commercial Natural Gas with +4F Temperature Scenario and Static Degree-day Sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	-13.9	-14.7	-13.4	-14.7	-14.2	-14.7	-12.7	-7.5	-8.9	-14.0	-14.7	-14.2	-14.7
NH	-18.3	-19.0	-17.3	-19.0	-18.4	-19.0	-17.3	-13.0	-15.9	-18.4	-19.0	-18.4	-19.0
VT	-12.0	-12.6	-11.5	-12.6	-12.3	-12.2	-10.5	-6.7	-8.6	-12.3	-12.6	-12.3	-12.6
MA	-11.9	-13.6	-12.3	-13.6	-13.2	-13.2	-7.4	-1.7	-2.9	-11.4	-13.6	-13.2	-13.6
CT	-11.3	-13.4	-12.2	-13.4	-13.0	-11.9	-5.0	-0.7	-1.2	-9.0	-13.1	-13.0	-13.4
RI	-14.0	-15.4	-14.1	-15.4	-15.0	-15.4	-10.6	-4.0	-5.1	-13.1	-15.4	-15.0	-15.4
NY	-7.4	-9.5	-8.6	-9.5	-9.2	-7.2	-1.9	-0.2	-0.2	-4.6	-8.8	-9.2	-9.5
NJ	-16.4	-18.9	-17.2	-18.9	-18.4	-16.8	-7.3	-1.2	-2.3	-12.6	-18.2	-18.4	-18.9
PA	-16.9	-18.3	-16.7	-18.3	-17.7	-16.8	-11.6	-6.4	-8.7	-16.2	-18.3	-17.7	-18.3
DE	-12.9	-14.5	-13.2	-14.5	-14.1	-13.6	-6.7	-1.8	-3.2	-10.9	-14.1	-14.1	-14.5
MD	-10.6	-12.6	-11.5	-12.6	-12.2	-10.6	-4.5	-1.1	-1.8	-7.6	-12.0	-12.2	-12.6
VA	-14.5	-16.7	-15.3	-16.7	-16.3	-14.9	-7.0	-1.6	-3.3	-11.0	-16.0	-16.3	-16.7
WV	-11.7	-13.0	-11.8	-13.0	-12.6	-11.6	-7.2	-3.8	-5.5	-10.6	-13.0	-12.6	-13.0
NC	-14.9	-17.7	-16.1	-17.7	-17.2	-13.8	-5.5	-0.9	-1.9	-9.8	-16.4	-17.2	-17.7
SC	-9.5	-11.9	-10.8	-11.9	-11.2	-8.5	-3.2	-0.7	-1.0	-6.0	-11.1	-11.6	-11.9
GA	-12.0	-16.0	-14.6	-15.3	-13.7	-7.8	-0.8	-0.3	-0.1	-2.9	-13.0	-14.6	-16.0
FL	-3.3	-5.6	-5.1	-5.5	-4.6	-2.4	-0.3	0.0	0.0	-0.1	-3.1	-5.0	-5.6

Table 59. Changes (%) in Commercial Natural Gas with +4F Temperature Scenario and Dynamic degree-day sensitivities in 2005.

	Annual	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ME	-16.8	-17.6	-16.0	-17.6	-17.1	-17.6	-15.2	-9.1	-10.8	-16.8	-17.6	-17.1	-17.6
NH	-20.2	-20.9	-19.1	-20.9	-20.3	-20.9	-19.1	-14.4	-17.5	-20.3	-20.9	-20.3	-20.9
VT	-12.8	-13.5	-12.3	-13.5	-13.1	-13.0	-11.2	-7.2	-9.1	-13.1	-13.5	-13.1	-13.5
MA	-12.0	-13.6	-12.4	-13.6	-13.2	-13.2	-7.4	-1.8	-2.9	-11.5	-13.6	-13.2	-13.6
CT	-11.1	-13.3	-12.1	-13.3	-12.9	-11.8	-4.9	-0.7	-1.1	-8.9	-13.0	-12.9	-13.3
RI	-19.4	-20.9	-19.1	-20.9	-20.3	-20.9	-14.5	-5.5	-7.1	-17.8	-20.9	-20.3	-20.9
NY	-3.5	-4.8	-4.3	-4.8	-4.6	-3.6	-0.9	-0.1	-0.1	-2.3	-4.4	-4.6	-4.8
NJ	-19.7	-22.1	-20.2	-22.1	-21.5	-19.7	-8.7	-1.4	-2.8	-14.9	-21.3	-21.5	-22.1
PA	-17.7	-19.0	-17.3	-19.0	-18.4	-17.5	-12.1	-6.7	-9.1	-16.9	-19.0	-18.4	-19.0
DE	-12.6	-14.2	-13.0	-14.2	-13.8	-13.3	-6.6	-1.7	-3.2	-10.7	-13.8	-13.8	-14.2
MD	-10.0	-12.0	-10.9	-12.0	-11.6	-10.0	-4.2	-1.0	-1.7	-7.2	-11.4	-11.6	-12.0
VA	-14.3	-16.6	-15.1	-16.6	-16.1	-14.7	-6.9	-1.6	-3.3	-10.9	-15.9	-16.1	-16.6
WV	-10.5	-11.9	-10.8	-11.9	-11.5	-10.6	-6.5	-3.4	-5.0	-9.7	-11.9	-11.5	-11.9
NC	-17.7	-20.6	-18.8	-20.6	-20.0	-16.2	-6.5	-1.1	-2.2	-11.5	-19.1	-20.0	-20.6
SC	-13.0	-16.1	-14.7	-16.1	-15.2	-11.6	-4.4	-1.0	-1.4	-8.2	-15.0	-15.6	-16.1
GA	-15.5	-19.7	-18.0	-18.9	-17.0	-9.8	-1.1	-0.4	-0.2	-3.7	-16.1	-18.0	-19.7
FL	-2.4	-4.1	-3.7	-4.0	-3.4	-1.7	-0.2	0.0	0.0	-0.1	-2.3	-3.7	-4.1

Glossary

Adaptation – "adjustments in ecological, social, or economic systems in response to actual or expected climatic stimuli and their effects or impacts. It refers to changes in processes, practices, and structures to moderate potential damages or to benefit from opportunities associated with climate change" (IPCC, 2001a).

Adaptive Capacity – **"**is the ability of a system to adjust to climate change, including climate variability and extremes, to moderate potential damages, to take advantage of opportunities, or to cope with the consequences" (IPCC, 2001a).

Balance Point Temperature – the average outdoor temperature at which energy for space-conditioning (heating, cooling, or both) is not required.

Base Temperature – the average outdoor temperature from which degree-days are calculated. See Balance Point Temperature.

Climate – "generalized statement of the prevailing weather conditions at a given place, based on statistics of a long period of record and including mean values, departures from those means, and the probability associated with those departures" (Strahler and Strahler, 1997).

Climate Change – a change of climate that is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and that is in addition to natural climate variability observed over comparable time periods.

Cold – the temperature at which energy is demanded for heating services as well as all temperatures below this temperature (i.e. range of temperatures below balance point temperature).

Cooling Degree-days – daily or accumulated daily (weekly, monthly, annual) temperature differences above a predefined base temperature.

Degree-days – daily or accumulated daily (weekly, monthly, annual) temperature differences from a predefined base temperature. In essence, they are indices of 'coldness' (heating degree-days) and 'hotness' (cooling degree-days).

Energy Demand Sensitivity – change in energy demand associated with a 100 unit change in degree-days.

Energy Demand Sensitivity Function – the underlying relation between energy demand and temperature which determines the Energy Demand Sensitivity and influenced by energy users' adaptations to climate.

Energy Demand Response – change in energy demand associated as determined by energy demand's sensitivity and adaptive capacity.

Heating Degree-days – daily or accumulated daily (weekly, monthly, annual) temperature differences below a predefined base temperature.

Hot – the temperature at which energy is demanded for cooling services as well as all temperatures above this temperature (i.e. range of temperatures above balance point temperature).

Mitigation – an anthropogenic intervention to reduce the sources or enhance the sinks of greenhouse gases (IPCC, 2001c).

Sensitivity – is the degree to which a system is affected, either adversely or beneficially, by climatic stimuli.

Vulnerability – "The degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity" (IPCC, 2001a).

Weather – "physical state of the atmosphere at a given time and place" (Strahler and Strahler, 1997).

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