

# **Building Science Atlas**

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# Preface

This is a Quarto book.

To learn more about Quarto books visit the [Quarto documentation on books](#).

# 1 Introduction

Welcome to the **Building Science Atlas**.

This collaborative repository compiles the current state of sustainability analysis for building science and urban analysis. We explore key questions from a systems and complexity perspective.

Our goal is to cover workflows, code, and theory—from the simplest ballpark estimates to complex simulation models.

## 2 Energy Demand

What is the energy demand of a building? This is one of the most common questions in building science.

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### 2.1 Simple Ballpark Estimates

To start, we look at the simplest way to get a ballpark number. This might involve looking at historical energy use intensity (EUI) for similar buildings in the same climate zone.

“A good estimate is better than a precise error.” - Anonymous Building Scientist

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Table 2.1: Typical Building Metrics

Building Type	Typical EUI (kWh/m <sup>2</sup> /yr)	Peak Load (W/m <sup>2</sup> )
Residential	100 - 150	40 - 60
Office	150 - 250	60 - 100
Retail	200 - 300	80 - 120

### 2.2 When to Attempt a Simulation

If a simple estimate is insufficient, a simulation may be necessary. We detail the different levels of complexity involved in simulating energy demand, starting from basic RC models.

### 2.2.1 RC Models (e.g., R51C)

RC (Resistance-Capacitance) models provide a simplified dynamic representation of a building's thermal behavior.

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### 2.2.2 Full Energy Balance

A full energy balance model considers all heat flows, internal loads, and HVAC system interactions.

The general heat balance equation can be expressed as:

$$Q_{load} = Q_{solar} + Q_{internal} + Q_{conduction} + Q_{ventilation} \pm Q_{storage} \quad (2.1)$$

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## 3 Simulation Workflows

If simulation is the goal, what are the different levels of complexity? We explore workflows for setting up and running building energy and urban simulations.

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### 3.1 Tools and Platforms

We rely on several open-source and widely-used tools in our field, such as:

- [Eddy3D](#)
- [Urbano](#)
- [EnergyPlus](#)

Each topic in this section will go from the most simple to the most complex analysis, describing what is involved to set it up.

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The calculation of mean radiant temperature ( $T_{mrt}$ ) is crucial in many of these tools:

$$T_{mrt} = \left[ \sum_{i=1}^n F_{p-i} T_i^4 \right]^{1/4} \quad (3.1)$$

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Figure 3.1: Simulation Workflow Overview

## 4 Neural Nets in Building Science

When classical simulation models reach their computational limits—such as in complex urban microclimates or real-time control applications—machine learning approaches offer a powerful alternative.

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This chapter covers the application of Artificial Neural Networks (ANNs) in building science.

“AI is the new electricity, and data is the new oil.” - Common ML Proverb

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A standard feedforward neural network layer can be expressed mathematically as:

$$h_{l+1} = \sigma(W_l \cdot h_l + b_l) \quad (4.1)$$

where  $h_{l+1}$  is the output,  $\sigma$  is the activation function,  $W_l$  are the weights, and  $b_l$  is the bias.

### 4.1 Physics-Informed Neural Networks

How can we embed the laws of thermodynamics into a neural network to predict energy consumption or indoor temperatures faster than an EnergyPlus run?

We will explore state-of-the-art physics-based deep learning approaches to these problems.

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Table 4.1: Common Hyperparameters for Building Energy Prediction

Hyperparameter	Typical Range	Description
Learning Rate	$10^{-4} - 10^{-2}$	Step size for gradient descent
Batch Size	32 - 256	Number of samples per update
Hidden Layers	2 - 5	Depth of the neural network
Units/Layer	64 - 512	Width of each hidden layer

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## 5 Summary

In conclusion, this repository represents an ongoing effort by students and researchers to document building science workflows.

By looking at particular questions from a systems and complexity perspective, we hope to provide a structured, curated guide for our field (Knuth 1984).

## References

Knuth, Donald E. 1984. "Literate Programming." *Comput. J.* 27 (2): 97–111. <https://doi.org/10.1093/comjnl/27.2.97>.