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Green IS, DSS & CyberGIS: Sustainable Growth and CO2 Reduction?

Christopher Franklin

Jayashree Sreedharan

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Completed Research Paper

Christopher G. Franklin
Naveen Jindal School of Management
University of Texas at Dallas
Cxf106020@utdallas.edu

Jayashree Sreedharan
School of Business,
University of Redlands
jayashree_sreedharan@redlands.edu

Abstract

A nonintuitive, decision support modeling ensemble approach is developed and tested for hypothetical, business-to-consumer (B2C,), innovative product data. The approach demonstrates the potential for gaining competitive advantage by integrating a unique permutation of innovation diffusion theory, sustainability, IS and location. The basic assumption is that early adopters of an innovation "pay more and buy less" i.e., which supports a firm's sustainable profitable growth while demanding fewer units due to their small proportion among all adopters which translates to reduced CO2 for their purchases. The behavioral rationale for early adopters is derived from Innovation Diffusion Theory. Locating all potential early adopters using the modeling ensemble (i.e., the Bass Bayes Spatial Extension) in a SOM (serviceable and obtainable market) temporally (i.e., quickly) and spatially (i.e., within qualified census blocks) is critical to optimum early adopter maximum target market penetration. The decision support modeling ensemble approach generates expected results subject to limits and delimits, ceteris paribus.

Keywords: Sustainable Growth, CO2 reduction, Bass, Bayes, CyberGIS, Innovation Diffusion Theory

Introduction

The paper is concerned with the development of a modeling ensemble that works as part of a decision support system (DSS) within a 3rd order Green IS ecosystem that has integrated a CyberGIS (see definition below) capability. It assumes large organizations (e.g., Apple or Tesla) with geo big data analytic needs. The focus is on the customer/marketing side of operations or what we refer to as the "demand chain" side of the "I.S. hill" (see Figure 1).

The solution applies a spatial analysis to the diffusion of an innovation utilizing the Bass forecasting and diffusion model with applied Bayesian logic to locate early adopters (the key players in this approach) by demographically qualified census blocks. Innovative products throttle pricing (drive up demand and prices) for sustainable profitable growth, while reducing the number of units demanded which ipso facto reduces the CO2/revenue ratio for a firm. A robust CyberGIS handles the complexities of temporal, spatial and demographic modeling data sets for innovative design/manufacturing/retailing organizations. The paper presents a limited and delimited worked example solution.

As a work-in-progress, the paper investigates location's role in a sustainable (Green) IS and in particular develops a limited hypothetical solution to demonstrate the process for potentially addressing current pressing global warming time constrained problems associated with climate change, by targeting different potential customers with innovative products.

To begin, Green IT and Green IS are different. To distinguish, ICTs (information and communications technologies) are "credited for creating 2 percent of the total CO2 emissions in the U.S." therefore, "Green IT seems to address a very small part of the overall climate change problem." Further, "By contrast, the use of Green IS throughout the economy potentially addresses much of 'the other 98 percent' of emissions." Green IS dwarfs Green IT as a focus for immediate CO2 remission, relief and reduction" (Dedrick, 2010). How can the Green IS/DSS + CyberGIS be visualized? We conceptualize Green I.S. as a "hill" metaphorically (see Figure 1), with back-side supply chain related processes and front-side "demand chain" processes.

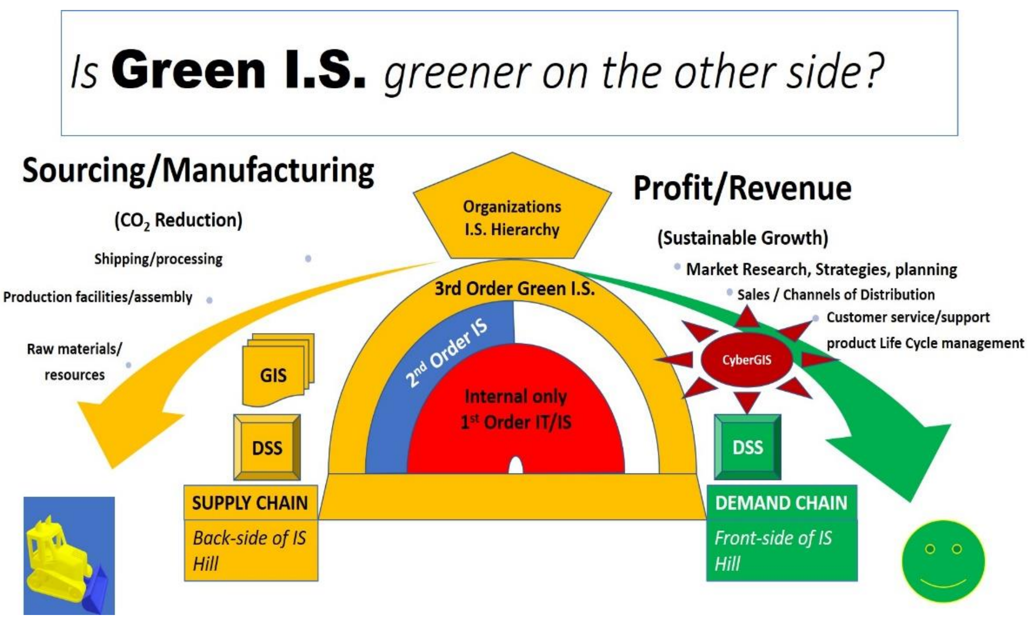

Figure 1. Conceptual "3rd Order Green IS/DSS & CyberGIS" Model

[Source: CyberGIS Center for Advanced Digital and Spatial Studies, University of Illinois at Urbana-Champaign, 2021)

The paper contributes to the literature in this interdisciplinary area by demonstrating the value and role that location and innovation diffusion theory can play when focusing on the "front-side" (i.e., the "demand chain" side) of a 3rd order Green IS as viewed through the lens of geospatial information sciences.

Research Problem/Question

Can Green-IS with advanced spatial data capabilities (i.e., CyberGIS enabled) and a geospatial information sciences compatible decision support system on the "demand chain" side of the IS hill, be employed to (a) empower a firm to improve its sustainable profits and growth, while simultaneously, (b) reducing its CO2/Revenue ratio by lowering the quantity of units necessary to be sold, to achieve the same or greater profits and growth?

Goal

The goal of the paper is to explore potential non-intuitive solutions to the challenge of global economic actors maintaining sustainable and profitable growth while lowering their environmental impacts (improving environmental sustainability e.g., CO_2 reduction). In other words, “create more economic value for an organization with less environmental impact (e.g., CO_2).

One of the spatial questions within the broader research question is “Can the customer facing side of the IS hill (i.e., the “demand chain” or marketing side) benefit an organization, from a 3rd order Green IS, spatially enable with GIS through a geospatial information sciences decision support lens, by locating more Early adopters/Innovators who fit the “sustainability profile, i.e., they pay more and in effect buy less CO_2?

Paper organization

The remainder of the paper is organized as follows: Definitions, a literature review, methodology, worked retail example, limits/delimits, findings, future research, conclusions, acknowledgements and references.

Invariant Word Symbol Definitions

2.1 Modeling Ensembles as distinguished from Ensemble Modeling

Unlike Ensemble modeling where each investigator (see Figure 2) is blind and attempts to extrapolate to the whole animal by studying just on aspect; our use of modeling ensemble referrers to each investigator not being blind and each part of the elephant is being studied by a specialist for that part.

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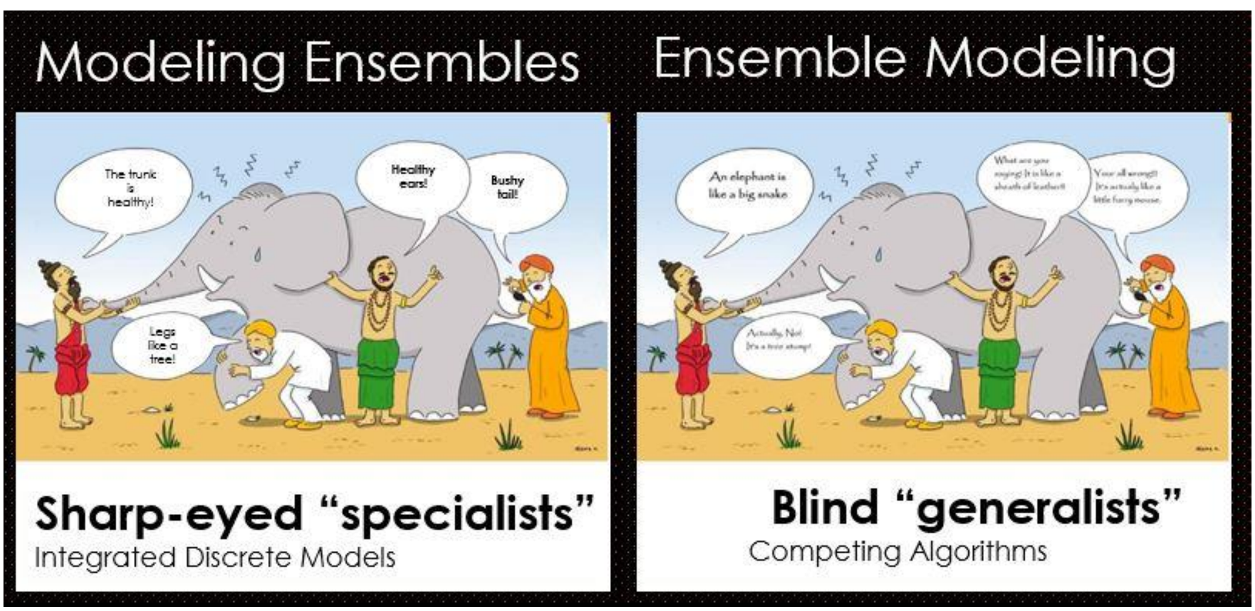

2.2 Green Information Systems (Green IS) & Green Information Technology (Green IT)

Green Information Technology (IT) refers to the practice and study of using IT and computer resources in a more environmentally responsible and effective manner. Green Information Systems (IS) generally refers to the use of IS to achieve environmental objectives. (Dedrick, 2010)

There is a hierarchy of IT/IS impacts on the environment (Hilty et al.,2006; Kohler and Erdmann, 2004). (1) First order effects relate to energy efficient IT hardware and recycling best practices. (3) Second order effects are those information and communications technology (ICT) effects on other processes and finally (3) in the longer term (likely where we are now), third order Green IS effects, which have a wider impact on changes in society like telecommuting and home-based businesses than Green IT.

2.3 Decision Support Systems and components

This refers to the overall decision support systems within an organizations Green IS but more specifically may include specific predictive methods and models when presented as Green IS/DSS. In this paper any implementation of this approach would include the BBSE (Bass Bayes Spatial Extension) integrated into the decision support dashboard of reports. For interconnection with a CyberGIS like platform-based ArcGIS "model builder" or some other algorithmic software would handle the location data and analytics.

2.4 CyberGIS

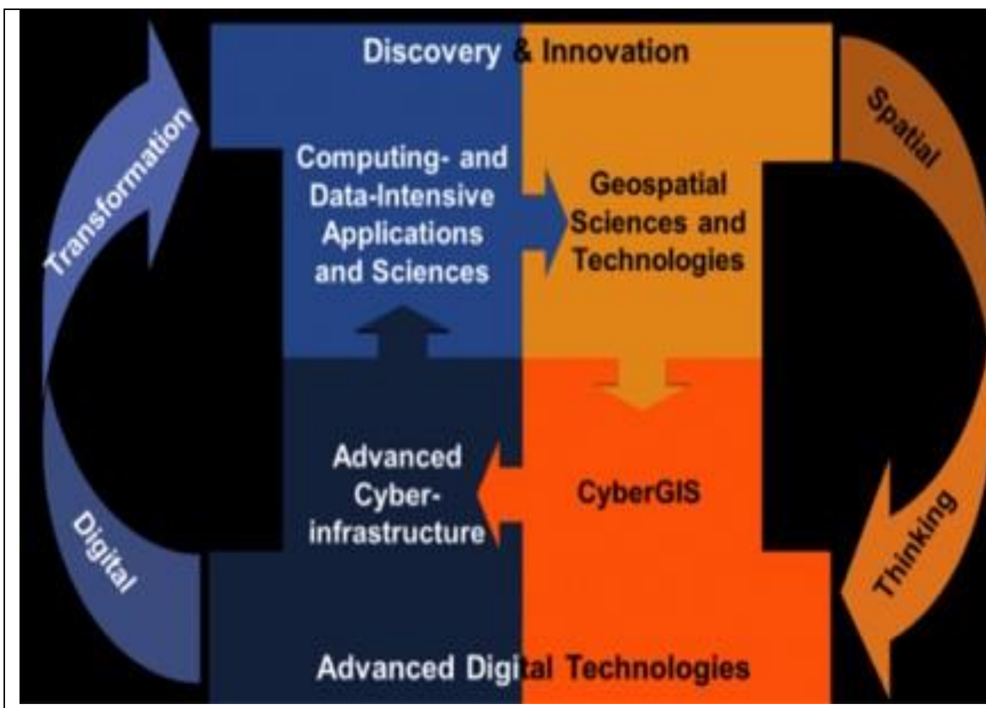

Figure 1. A CyberGIS Conceptual Model

[Source: CyberGIS Center for Advanced Digital and Spatial Studies, University of Illinois at Urbana-Champaign, 2021]

The rational for a "Cyber" GIS is based on heteroskedastic spatial-temporal environmental variables rapidly moving through periodic phases of equilibria and then change, at multiple scales and dimensions. The variables are permutationally and dynamically changing in heterogeneous environments: climate change/global warming, environmental pollution, famine, hunger, drought and population impacts. These are of course by nature extremely complex and sensitive to initial conditions (as in Chaos Theory) and therefore enormously spatial-temporally complex both in terms of consistency of data quality and quantity they produce for study. Location awareness and proximity intelligence (aka Location Intelligence) are critical to understanding these variable forcings. New approaches and creative problem solving and spatial thinking are needed here.

> *"To tackle these challenges, which exhibit tremendous geo and spatial complexity, requires critical knowledge of spatial patterns and their driving processes across a number of spatial and temporal scales by combining rich spatiotemporal data, analytics and models to form novel problem-solving approaches enabled by cyberGIS." (Wang, 2021)*

2.5 Market Potential and Opportunities

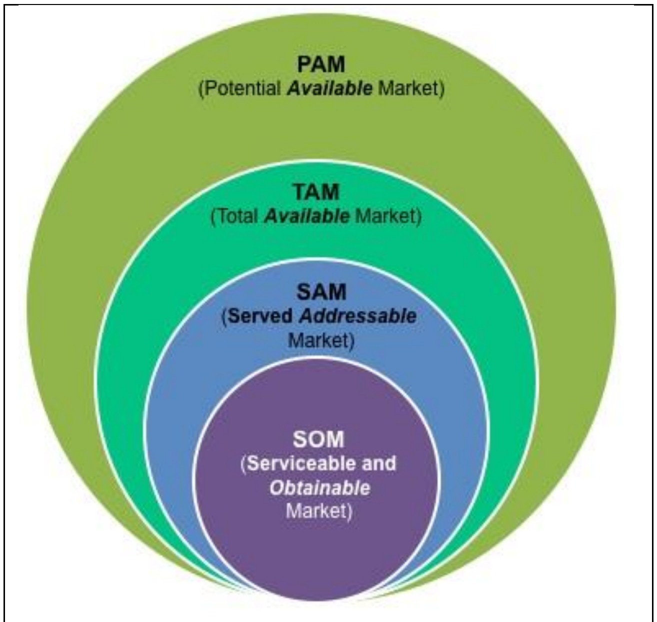

Figure 3. Modified Research Model

[Source:https://www.marketingstrategy.com/understanding-and-using-tam-sam-and-som]

In order to understand this transdisciplinary approach a basic understanding of marketing terms is required. Potential Available Market (PAM) is the global size of a market. Total Available Market (TAM) is the potential revenue or units demanded limited to the geography your firm can service. Service addressable Market (SAM) is the limited geographic market, delimited for specific sectors. While Serviceable and Obtainable Market (SOM) or Market Share is the limited and delimited market further reduced by any constraints in a firm's resources that would reduce the target market within key market segments. This estimate is essentially a firm's business plan and goal.

The terms (1) available, (2) addressable and (3) obtainable refer to the following respectively:

- An upper limit on market opportunity long term
- The potential market that could be addressed

- The realistic expectation of sustainable profits and growth subject to limitations, delimitations ceteris paribus.

Understanding the implications of the modeling ensemble and the effects of innovation diffusion theory requires some appreciation for how a market is formed and estimated (Douglas, 2018).

Literature Review

Green IT and hierarchical Green IS

According to (Hilty et al.,2006; Kohler and Erdmann, 2004) there are three levels (i.e., a hierarchy) of IT impact on the environment. First order effects relate to energy efficient IT hardware and recycling best practices. Second order effects are those ICTs effects on other processes. And finally, in the longer term (likely where we are now) third order Green IS effects have a wider impact on changes in society like telecommuting and home-based businesses.

Bass Diffusion Forecasting Model

Early diffusion research in the marketing discipline was rare (Rogers 2004). Bass built upon the ideas of Fourt, Woodlock (1960), Mansfield (1961), and initial discussions with Rogers (1962), as well as transdisciplinary work from epidemiology (BBRI, 2010) and his impact was such that by 2003, approximately 16% of 5,200 diffusion publications were focused exclusively on marketing innovation diffusion studies, as a result of the Bass diffusion model (Rogers 2004).

"The Bass Model is the most widely applied new-product diffusion model. It has been tested in many industries and with many new products (including services) and technologies." (BBRI, 2010). The Bass diffusion model calculates the timing and quantity of Adopters/Adoptions occurring during the diffusion of an innovative product (BBRI 2010). The Bass model has several alternate forms (Ibid.). This paper utilizes the Robinson, Lakhani (1975) formulation:

$$n(t) = \left[p + \left(\frac{q}{M}\right) N(t-1)\right] [M - N(t-1)] \tag{1}$$

Where:

- "t" - refers to the time step (including zero) of adoption activity, a succession of one-time acts of acquiring the innovation under study
- "M" - potential market refers to "total adoptions". Estimated by management through surveys, subjective evaluation or a combination of techniques (BBRI 2010)
- "p" - the "coefficient of innovation"
- "q" - the "coefficient of imitation" - determined through experimentation, curve fitting and/or by studying analogous products
- "n(t)" - refers to either "Adopters" or "adoptions" (where "Adopter" makes one and only one acquisition)
- "N(t-1)" - cumulative adoption/adopter function

  "The theory stems mathematically from the contagion models which have found such widespread applications in epidemiology." (Bass 1967).

Also, the Bass model is “aspatial” and presents only “temporal” forecasts of adopters/adoptions (i.e., Innovators and Imitators) (BBRI 2010).

The model relies on a number of assumptions:

1. It is delimited mathematically by its parameters: i.e., "p", "q" and "M"
2. The ultimate number of Adopters "M" must be known beforehand (i.e., the S.O.M.) or estimable for proper calibration of the model. Thus, M's consists of those who have adopted and those who have not yet adopted.

3. The model is limited to first time purchases of new innovative products and assumes that sales of a new product are primarily driven by "word-of-mouth" (WOM) from satisfied customers" (BBRI 2010).
4. "...the probability of adopting by those who have not yet adopted is a linear function of those who had previously adopted." (BBRI 2010) i.e., the model assumes "the timing of a consumer's initial purchase is related to the number of previous buyers" (Bass 1969).
5. The model assumes constant pricing with inelastic demand although the "innovators" demand curve begins highly inelastic and gradually transitions to one that is highly elastic.
6. The model lacks any spatial connection to assist in spatial analytics of the shape and structure of market area development.

The following example illustrates how the model works. Table 1 and Figure 1 represent a Bass diffusion forecast for an innovation over 14 Bass time intervals, from initial Bass time period t0 (with a positive Y-intercept value) to t13.

Period	Time	Innovators	Imitators	Adopters
t_0	0	80	0	80
t_1	1	74	37	110
t_2	2	65	77	142
t_3	3	53	111	164
t_4	4	40	125	165
t_5	5	24	112	139
t_6	6	16	80	96
t_7	7	8	46	55
t_8	8	4	23	27
t_9	9	2	11	12
t_{10}	10	1	5	5
t_{11}	11	0	2	2
t_{12}	12	0	1	1
t_{13}	13	0	0	0
	Total	**370**	**630**	**1000**

Table 1. Fourteen Bass Periods (Franklin, 2018)

The three parameters used to obtain this hypothetical Bass model forecast are the "coefficient of innovation", (p=0.08); the "coefficient of imitation," (q=0.5) and the "potential adopter market", (M=1000) typically estimated from empirical surveys or subjective retail analyst evaluations (BBRI 2010). The model distinguishes between two types of Adopters: "innovators" and "imitators". Innovators are defined as those who have a high personal trait of "innovativeness" and are first movers in a market to purchase innovations (Hägerstrand 1968; Rogers 1958). "Innovators" also, and importantly, have characteristically low risk aversion usually correlated to high socioeconomic means and status (Ibid). An additional key trait is that "Innovators" do not rely on the purchase choices of others (unlike imitators or "followers", who are greatly influenced by the opinions of others through word-of-mouth because of a generally very high level of risk aversion (Ibid).

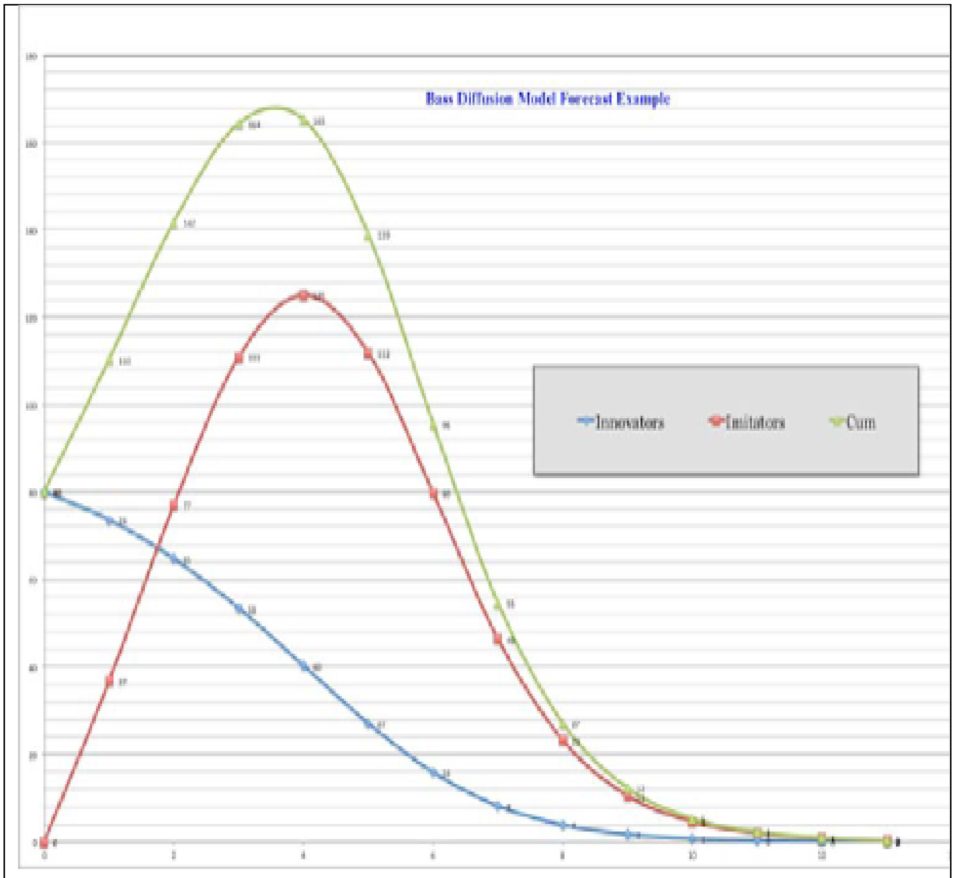

Figure 3. Time Series Adopter Graph (Franklin, 2018)

3.3 Bayes Theorem

1. **Bayes' Theorem**

"There is no dispute over the mathematical validity of Bayes' Theorem, which is a direct consequence of the definition of conditional probability. It would also be generally agreed that Bayes' Theorem is applicable in the…", classic three-machine factory example (Kalbfleisch, J. G. 2012).

Bayes' theorem has been used to solve many search and rescue problems as well as recovery e.g., location of the sunken Titanic and missing US Navy submarines. (McGrayne 2011). In fact, Alan Turing "broke" the German Nazi "enigma code" machine during WWII using the non-intuitive "inverse probability" of Bayes' theorem, which was still top secret until relatively recently (Stone, 2016).

Bayesian principles in terms of psychology have been long understood in areas like Brain science, confirming the human brain utilizes Bayesian principles in all of its pattern/problem solving and recognition (Seth, 2012).

Bayes' theorem has emerged "...as a powerful tool with a wide range of applications...machine learning, epidemiology, psychology, forensic science, human object recognition, evolution, visual perception, ecology..." (Stone 2016).

To obtain a high spatial-temporal resolution, Bayes' theorem (Bayes, 1763) is applied dynamically to Bass model outputs, at each Bass time step, in combination with new empirical "evidence" (i.e., geocoded sales of innovation adoption) to adjust posteriors distributions. The Bass model output is spatialized, simply by allocating Adopters to qualified census blocks (QCBs). A posterior probability distribution is calculated while implementing the law of total probability. Repetition of the interactions from each Bass period provide an evolving trade area map from which Imitators and Innovators can be selected using likelihood ratios developed from the heteroskedastic variability found in the numbers of Imitators and Innovators.

"As Bayesians, we start with a belief, called a prior. Then we obtain some data and use it to update our belief. The outcome is called a posterior. Should we obtain even more data, the old posterior becomes a new prior and the cycle repeats." (Zajac 2016).

Spatial distribution of Bass adopters begins after empirical sales have initiated. The empirical sales (or Adoptions) create "qualify census blocks" (QCBs), where at least one adopter's innovation purchases have occurred.

A "prior" is updated with new sales evidence (and by definition the spatial information associated with the census block is then available also). Each new empirical sale of the innovation to an Adopter changes the priors and thus the posteriors on which successive generations of the Bass spatial allocation is based; while providing "new and improved beliefs" about the spatial allocation of Adopters by "modifying initial beliefs" (McGrayne 2011).

Figure 4 is a simple conceptual visualization of the Bass-Bayes Spatial Extension process.

Figure 4. Conceptual Model of the Bass-Bayes Spatial Extension

Bayes' theorem can be written mathematically in several forms (Anderson, Sweeney, Williams 1984):

$$Pr(A_i|B) = \frac{Pr(A_i)(B|A_i)}{Pr(B)} \quad (2)$$

This is the alternate Bayes' theorem generalized form (Ibid.):

$$Pr(A_i|B) = \frac{Pr(A_i)\,Pr(B|A_i)}{Pr(B|A_1)Pr(A_1)+Pr(B|A_2)Pr(A_2)+\cdots+Pr(B|A_n)Pr(A_n)} \quad (3)$$

for $i = 1,2,\ldots,n$.

"Pr" refers to the probabilities of the events Ai and B where Pr (B) ≠ 0. Pr (Ai) is the prior probability distribution "...where the intermediate stage permits k different alternatives (whose occurrence is denoted by A1 , A, ..., Ak)." (Freund 2004).

This generalization "requires the following theorem, sometimes called the rule of total probability or the rule of elimination. If the events A1 , A2, ... and Ak constitute a partition of the sample space S and Pr (Ai) ≠ 0 for i =1,2,...,k, then for any event A in S ...the A's constitute a partition of the sample space if they are pairwise mutually exclusive and if their union equals S." (Freund 2004). The Pr (A1) and Pr (B) are independent probabilities of observing event "A" and event "B", respectively. Pr (B | Ai) is a conditional probability distribution of the likelihood of event B occurring if Ai occurs; and Pr (Ai| B) is the posterior probability distribution for the likelihood of Ai given B (Ibid.). Table 2 shows the calculations for a factory with three stand-alone machines (A1, A2, A3), all of which produce some small percentage of defective items (Kalbfleisch, J.G. 2012). Total output for all three machines is 1000 items distributed as follows:

- Machine 1. Pr (A_1) = 200/1000 or 20% or 0.2
- Machine 2. Pr (A_2) = 300/1000 or 30% or 0.3
- Machine 3. Pr (A_3) = 500/1000 or 50% or 0.5
-

1	2	3	4	5	6	7	8
Producing	Items	**PRIOR** %	Event A i Marginal	Adopter/	Conditional	Event B Joint	**POSTERIOR** Marginal
Units	Prod	Distribution	Pr (Ai)	QCB	Pr (B | Ai)	Pr (B | Ai) x Pr (Ai)	Pr (Ai | B)
Machine-1	200	0.2	0.2	10	0.05	0.010	0.417
Machine-2	300	0.3	0.3	9	0.03	0.009	0.375
Machine-3	500	0.5	0.5	5	0.01	0.005	0.208
	1000	1	1	24		**0.024**	1
						Pr (B)	

Table 2. Classic Bayesian 3-Machine/Defect Example

Consider the following question: If one item is selected randomly from the total items produced (i.e., 1000 items) and is found to be defective, what is the likelihood that Machine 3 produced the defective item?

The inverse probability Bayesian mechanism (i.e., P (A1|B), allows this question to be answered i.e., "What is the probability A1 is correct, given that B has occurred?" In this example substituting the values, the likelihood was 50% (i.e., the Prior) that Machine 3 produced the defect, but with the empirical evidence (from column 6) of defect rates for Machine of 1%, the likelihood Machine 3 produced the defect has dropped to 20.8%; making Machine 1 (i.e., at 41.7% the most likely candidate for making a defect item).

This is a non-intuitive answer. It is sometimes referred to as "inverse probability". However, the ability to ask "and" answer this question correctly is both a necessary and sufficient condition to allocate a spatial location to a Bass Adopter (or for "any" temporal only aspatial forecasting model output).

In other words, it can be seen in Table 2 that (before any new evidence), the most likely machine to produce a defect is A3 (Why? Because it produces 50% of all items produced). However, after updating the model with new "defect rate" evidence (see Table 2, Column 6) the most likely machine to produce a defect is not " A3 " but rather " A1 " at 41.7% (Table 2, Column 8).

The evidence that leads to these posterior probabilities is derived from quality control procedures that track the actual dynamic defect rates as equipment ages (e.g., cutter tool wear, blade breaks and worn-out drill bits), to establish the conditional probability Pr (B| Ai). This enables computation of joint probabilities [Pr (B|Ai)) Pr (Ai)] for each machine and finally to calculate the overall defect probability (i.e., Pr (B)), which is also the normalizing constant.

Bass Bayes Spatial Extension - BBSE

Bass-Bayes Spatial Extension (BBSE)

The Bass diffusion model specifically lacks any explicit spatial context. However, the Bass model can be spatially invoked in the same way that the Three-Machine/Defect problem (Kalbfleisch 2012) can be structured spatially, if Euclidean distance were recorded for each machine in terms of its distance from the factory center point.

Utilizing this simple analog overcomes the "aspatial" Bass delimitation, and allows Bass to function within the context of the increasing availability of spatial-temporal data and information components.

The Bass-Bayes Spatial Extension (BBSE) approach operates parsimoniously based on the following assumptions.

- Assumption 1: The Bass Diffusion Model is both a necessary and sufficient condition for forecasting and predictive formulation, correctly estimating the timing and quantity of first-time Adopters (Imitators and/or Innovators) of an innovative product or service, throughout a store level trade area (SLTA) as defined by the Bass diffusion model.
- Assumption 2: There exists ongoing, geo-coded empirical, sales transaction data or "evidence" which provides the likelihood of the hypotheses being true. These initial random empirical adoptions of the innovation thus "qualify" certain census blocks in the store level trade area as "QCBs" for receipt of Bass predicted Adopters, after the innovation is released to begin diffusion.
- Assumption 3: We assume all Bass adopters are initially located in the store's census block (Note: this is an initializing placeholder condition only) until there is intervening evidence (i.e., empirical innovator sales transactions), in a Bass period to allow additional new QCB(s) into the innovation diffusion trade area shape. Gelman (2008b) points out that utilizing a "placeholder" for initializing Bayesian iterations is valid and has little or no distinguishing effects on evolving equilibria.

This is because a placeholder operates in a similar fashion to a statistical weighted in which each term of the average becomes relatively less important as new additional terms are added and the "weight" is spread across all terms.

Methodology

Research Objectives

Utilizing IS and location (i.e., GIS) capability to improve sustainability of profitable growth and environmental impacts has several well documented case studies beginning in the 1980s (e.g., J.D. Irving, Saint John, New Brunswick). This example and many others have successfully integrated this capability on what we refer to as the traditional “back-side” of the information systems “hill” in an organization (i.e., the “supply chain” side of the business)

Our novel research objective in this paper is to investigate what, if any, ability exists to apply IS, sustainability and location to the so-called “front-side” of the information systems “hill” in an organization (i.e., the customer-facing, “demand chain” side of the business).

Innovative “front-side” of the information systems hill – 3rd Order Green IS/DSS and CyberGIS

We adopt the limits/delimits of innovation diffusion theory to apply the DSS Bass Bayes Spatial Extension engine within 3rd order Green IS to see if selecting certain “types” (i.e., early adopters) of potential customers to market to has some positive effect on sustainability, through the power of the IS/specialized DSS components and CyberGIS integration.

Worked Retail Example (Green IS, DSS & CyberGIS)

The following explains procedures to spatially allocate the quantity of Bass forecasted Adopters per Bass time period, using the Bayesian process. The main purpose in allocating Bass Adopters to specific "qualified" census blocks is to support the microanalytic study of the spatial-temporal impacts during (a) each Bass period and (b) across all Bass time periods longitudinally (to eventual market equilibrium) within the "shape" of the innovation diffusion trade area.

For ease of explanation, Table 3 assumes the same values as the Three-Machine/Defect problem example, (i.e., Table 2). However, in this example, assume a hypothetical home improvement/home-center retail store location in Southern California. Table 3 presents the tabular calculations necessary for Bayesian posteriors to be calculated for Bass time period 4. Within the store level trade area (SLTA) of this hypothetical store, a trade area "shape" has emerged based on empirical sales of the innovation. The trade area "shape" is made up of the following Qualified Census Blocks (QCBs) or "producing units" at Bass Period 4. The three (3) QCBs are (A1, A2, A3).

1	2	3	4	5	6	7	8
		PRIOR	Event Ai			Event B	**POSTERIOR**
Producing Units	Census Blk. POP	% Distribution	Marginal Pr (Ai)	Adopter/ QCB	Conditional Pr (B | Ai)	Joint Pr (B | Ai) x Pr (Ai)	Marginal Pr (Ai | B)
QCB-A1	200	0.2	0.2	10	0.05	0.010	0.417
QCB-A2	300	0.3	0.3	9	0.03	0.009	0.375
QCB-A3	500	0.5	0.5	5	0.01	0.005	0.208
	1000	1	1	24		**0.024**	1
						Pr (B)	

Table 3. Simplified Bass-Bayes Spatial Extension Example Franklin 2021

But how does the **application of location** (i.e., GIS) and the **Bass Model** identification of WHO (i.e., Innovators or Imitators as the adopter market changes for your innovation each successive Bass period), or WHEN (i.e., what is the heteroskedastic ratio at any Bass period for Innovators in your market given the half lie of an innovator is roughly 2 Bass periods) with the **Bayesian** conditional probability of the changing likelihood of clusters of Innovators being in any specific qualified census block (QCB) (see Table 3) relate to the logic that "Innovation throttles and reduces the number of early buyers? The answer to this question resides in a thorough understanding of Innovation Diffusion Theory. There are significant references to allow the reader to further study these effects, which are critical to understanding the approach developed in this paper.

Knowing the location of REA's can assist in an innovation diffusion "steerage and throttling effect" (Allaway et al., 1994).

Implementing the Bass-Bayes Spatial Extension for achieving spatial allocations is accomplished again utilizing the "inverse probability" feature of Bayes theorem. First consider a simple but classic three-machine factory defect example (Kalbfleisch, J.G., 2012). The objective is to answer the following critical question: "Given a randomly selected defective item (from all items produced by three machines), what is the probability a defective item, was produced by Machine #3".

Translating the Three-Machine/Defect problem example into the Bass-Bayes Spatial Extension (BBSE) worked retail Store Level Trade Area (SLTA) example:

1. "Qualified census blocks" (QCBs) equate to Machines
2. Adopters who have made empirical purchases of the innovation are considered to be the "defective items" within the QCB's population.

NB The classic machine-age analogy may lack elegance, but it serves from a practical perspective, to demonstrate the functional equivalence of census blocks and machines. The analog of “machines wearing out over time and producing some percentage of defects” is mirrored by “QCB’s ‘wearing out’ over time (i.e., changing their compositional core demographics over time like socioeconomic status) and producing some percentage of defects (i.e., adopters).

Recall a QCB (i.e., qualified census block) is defined as a special census block, which has at least one empirical first-time Adopter (of the innovation) and who is located within the qualified census block i.e., within the polygonal defined areal geo-boundary of the census block.

It is also important to note that a home improvement store sells, delivers and installs special order fenestration products (e.g., custom exterior doors and windows) mostly to DIFM (i.e., Do- It-For-Me) type customers; who can afford to purchase both the product and the installation contract to have the innovation installed. Thus, again the geo-coded location of the Adopter is known and must be identifiable for this methodology to operate.

Census blocks have important geospatial statistical attributes. Thus, each empirical DIFM (do-it-for-me) Adopter, by definition is from a QCB that has critical census demographic data, has a specific and known geocoded residence address (required for installation of the innovation). Thus, the spatial location of the Bass empirical Adopter’s census block is known.

Empirical Adopters (or as defined in the classic 3-Machine/Defect problem example - "defects") make purchases of the innovation for a specific QCB.

Thus:

1. QCBs = Machines
2. Bass Adopters = Defects

Once "Adopters" are linked to specific "qualified census blocks", the Adopter instantly becomes "spatially allocated" with a probability associated with their location. Recall the objective is to answer the following critical question: *"Given a randomly selected Bass Adopter (from all Bass Adopters “produced” by QCB’s), what is the probability the Bass Adopter was QCB #XXX?"*

With these facts, the following critical Bayesian question can be posed to establish the probability an Adopter is in a specific Qualified Census Block. "If a population member is selected at random from the total population of all three QCBs, and is found to be a Bass Adopter; what is the probability the Bass Adopter came from QCB- A3?"

Using Bayesian logic and looking at just the "prior" population distribution, the Bass Adopter allocation would likely be in the same proportion or ratio as the population distribution in each QCB; i.e., Pr (Ai) see column 3 of Table 3, i.e., 20%.

However, with new evidence (e.g., a new empirical Adopter sale in one of the existing QCBs or in a new QCB for example), Table 3 is updated with new evidence and the posteriors calculated. For Pr (Ai| B) see column 8 of Table 3, i.e., 41.73%.

Thus, in the classic Bayesian logic and based on evidence, we now see the probability for a specific QCB “hosting” a Bass Adopter has increased from 20% to 41.73% - the probability has doubled. These calculations in detail are captured in Table 4. below.

This changes our spatial thinking, our management decision making options and the likely best choices for “quickly” harvesting the naturally dissipating Bass Adopters.

By way of example this problem and solution is similar to the marketing problem that exists in the pharmaceutical industry where it is critically important to quickly find doctors (word of mouth opinion leaders) who will write prescriptions of new drugs and then explore their social networks as influencers to find second and third tier doctors who can be influenced by the opinions of "early adopters" to consider prescribing new drugs. Again, time is of the essence in this approach.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	TIME	DEFECT						BAYES THEOREM CALCULATIONS													
2		ADOPTER		BASS	%																
3		EMPIRICAL	EVENT	"M"	Potential	PRIOR	CONDITIONAL	JOINT	POSTERIOR	POSTERIOR	EVENT										
4		SALES		Adopters	CONSUMERS	P(Census Tract i)	P(Customer/Census Tract i)	P(Customer/Census Tract i) P(Census Tract i)	P(Census Tract i/ Customer)	%			S	A	B	C		S	A	B	C
5		COUNT		POP	Pr (A)							Innovators					Imitators				
6	t_0	1	Store BLOCK A	1	100.0%	1.0000	1.0000	1.000	1.00000	100.0%	Store BLOCK A	80	80				0				
7		1		1				P(B)	1.00000			80					0				
8								1.000													
9																					
10																					
11	t_1	1	Store BLOCK A	1	0.0%	0.0002	1.0000	0.000	0.00111	0.1%	Store BLOCK A	80	0				0	0			
12		30	Census BLOCK A	200	100.0%	0.9998	0.1500	0.150	0.99889	99.9%	Census BLOCK A	74		154			37		37		
13		31		201	100.0%			P(B)	1.00000	100.0%	Total	154					37				
14								0.150													
15																					
16																					
17	t_2	1	Store BLOCK A	1	0.0%	0.0001	1.0000	0.000	0.00089	0.1%	Store BLOCK A	80	0				0	0			
18		15	Census BLOCK A	200	25.0%	0.2500	0.0750	0.019	0.19982	20.0%	Census BLOCK A	74		44			37		23		
19		30	Census BLOCK B	300	75.0%	0.7499	0.1000	0.075	0.79929	79.9%	Census BLOCK B	65			175		77			91	
20		46		501	100.0%			P(B)	1.00000	100.0%	Total	219					114				
21								0.094													
22																					
23																					
24	t_3	1	Store BLOCK A	1	0.0%	0.0000	1.0000	0.000	0.00038	0.0%	Store BLOCK A	80	0				0	0			
25		40	Census BLOCK A	200	36.4%	0.3636	0.2000	0.073	0.61515	61.5%	Census BLOCK A	74		167			37		##		
26		30	Census BLOCK B	300	40.9%	0.4091	0.1000	0.041	0.34602	34.6%	Census BLOCK B	65			94		77			78	
27		10	Census BLOCK C	500	22.7%	0.2273	0.0200	0.005	0.03845	3.8%	Census BLOCK C	53				10	111				9
28		81		1001	100.0%			P(B)	1.00000	100.0%	Total	272					225				
29								0.118													
30																					
31																					
32	t_4	1	Store BLOCK A	1	0.0%	0.0000	1.0000	0.000	0.00013	0.0%	Store BLOCK A	80	0				0	0			
33		60	Census BLOCK A	200	25.5%	0.2553	0.3000	0.077	0.46747	46.7%	Census BLOCK A	74		146			37		##		
34		50	Census BLOCK B	300	31.9%	0.3191	0.1667	0.053	0.32463	32.5%	Census BLOCK B	65			101		77			##	
35		40	Census BLOCK C	500	42.6%	0.4255	0.0800	0.034	0.20777	20.8%	Census BLOCK C	53				65	111				47
36												40					125				
37		151		1001	100.0%			P(B)	1.00000	100.0%	Total	312					350				
38								0.164													

Table 4. Allocating Bass Forecasted

Table 5. Excel Formulas for Table 4

	J	K	L	M	N	O	P	Q	R	S	T	U
1												
2												
3	POSTERIOR	EVENT										
4	%			S	A	B	C		S	A	B	C
5			Innovators					Imitators				
6	=I6	Store BLOCK A	43	=$J$6*$L$7				0				
7			=SUM(L6)					0				
8												
9												
10												
11	=I11	Store BLOCK A	43	=$J$11*$L$13				0	=$J$11*$Q$13			
12	=I12	Census BLOCK A	41		=$J$12*$L$13			10		=ROUNDUP($J$12*$Q$13,0)		
13	=SUM(J11:J12)	Total	=SUM(L11:L12)					=SUM(Q11:Q12)				
14												
15												
16												
17	=I17	Store BLOCK A	43	=$J$17*$L$20				0	=$J$17*$Q$20			
18	=I18	Census BLOCK A	41		=$J$18*$L$20			10		=$J$18*$Q$20		
19	=I19	Census BLOCK B	38			=$J$19*$L$20		21			=$J$19*$Q$20	
20	=SUM(J17:J19)	Total	=SUM(L17:L19)					=SUM(Q17:Q19)				
21												
22												
23												
24	=I24	Store BLOCK A	43	=$J$24*$L$28				0	=$J$24*$Q$28			
25	=I25	Census BLOCK A	41		=$J$25*$L$28			10		=$J$25*$Q$28		
26	=I26	Census BLOCK B	38			=$J$26*$L$28		21			=$J$26*$Q$28	
27	=I27	Census BLOCK C	35				=$J$27*$L$28	31				=ROUNDUP($J$27*$Q$28,0
28	=SUM(J24:J27)	Total	=SUM(L24:L27)					=SUM(Q24:Q27)				
29												
30												
31												
32	=I32	Store BLOCK A	43	=$J$32*$L$37				0	=$J$32*$Q$37			
33	=I33	Census BLOCK A	41		=$J$33*$L$37			10		=$J$33*$Q$37		
34	=I34	Census BLOCK B	38			=$J$34*$L$37		21			=$J$34*$Q$37	
35	=I35	Census BLOCK C	35				=$J$35*$L$37	31				=ROUNDUP($J$35*$Q$28,0
36			32					41				
37	=SUM(J32:J35)	Total	=SUM(L32:L36)					=SUM(Q32:Q36)				
38												

Table 5. Excel Formulas for Table 4

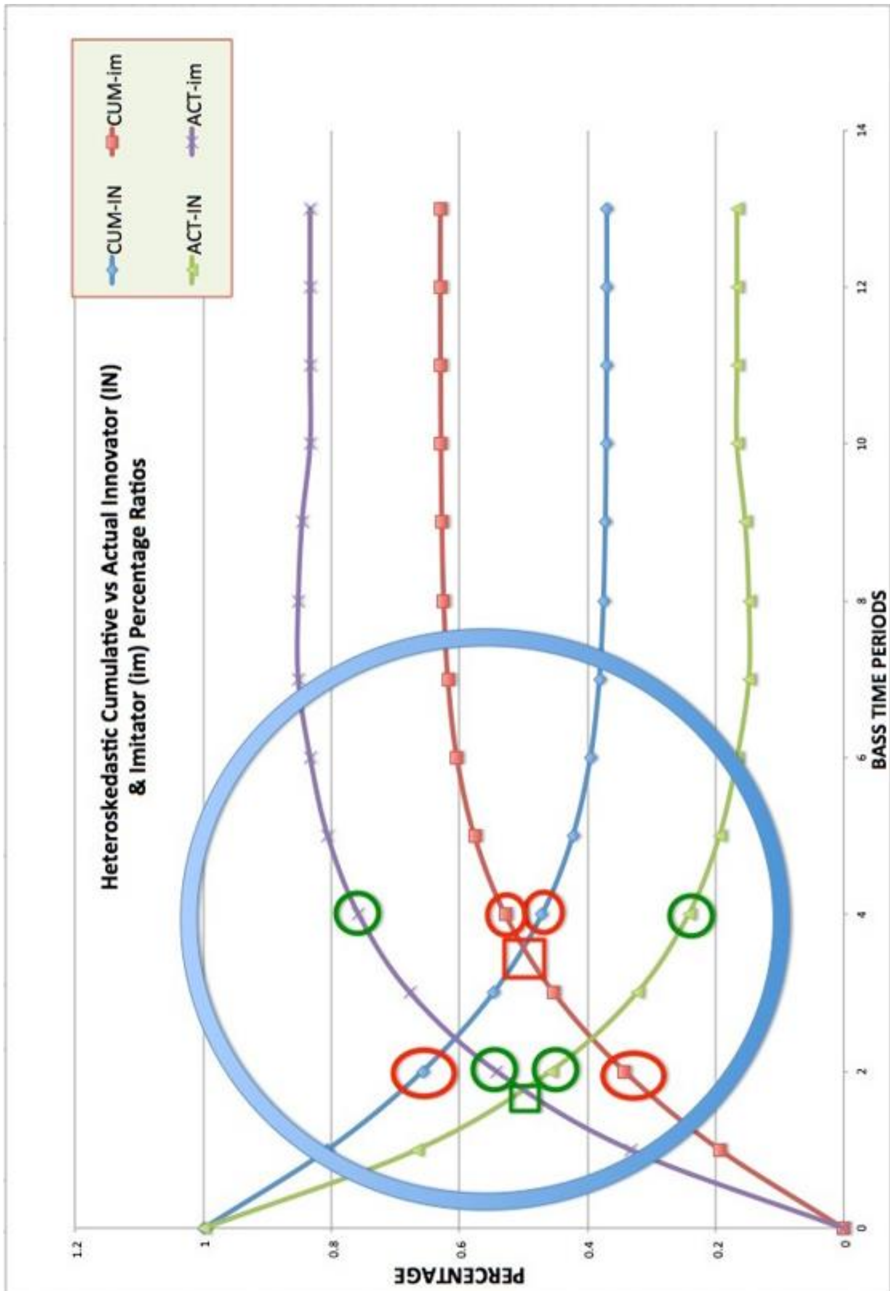

Figure 5. Heteroskedastic Ratio Variability for Innovators and Imitators

This can be seen in the green ACT-IN (i.e., ACTUAL-INNOVATORS) and the purple ACT-im (i.e., ACTUAL-imitators) curves. Reading from the Table 6 graph, the 50-50 ratio proportion (of Innovators to Imitators) for "CUM's" is reached approximately just before the 4th Bass period, while the "ACT's" 50-50 equivalence is reached just before Bass period 2, as can be approximated from studying the Table 6 graph.

This provides the retail practitioner with "advanced" warning. The "advanced" warning suggests that current forecasted customers coming to the store to adopt the innovation have lost a lot of their **Innovator energy force** or sense of purchase urgency and/or **price and risk insensitivity**.

Thus, the REA (random empirical adopters) probably will exhibit more of the "imitator" lack of urgency with high price and risk sensitivity after Bass time period two (2).

But this also suggests that the store's innovation campaign will still have two (2) more Bass periods (i.e., approximately to Bass time period four (4), in the trade area "mixture pool" of potential adopters, to enjoy a higher than 50-50 percent **Innovator type adopter** demand in which intervention and various targeted merchandising and marketing mechanisms can extend the "harvest" of the higher proportion Innovator (i.e., Early Adopter) presence. Secondly, the cumulative heteroskedastic ratio (see Figure 5) for Innovators and for Imitators can be treated as the probability that an adopter selected at random from the "mixture pool" will be an Innovator OR Imitator.

Therefore, by definition, in the early stages of an innovation diffusion, the likelihood will be high that a random selection of an adopter from the "mixture pool" will be an Innovator (i.e., Early Adopter) and as the diffusion progresses past Bass time period four (4) the likelihood will shift rapidly to a random selection of an adopter from the "mixture pool" being an Imitator, based simply on the population, over time, of each type of adopter in the trade area "mixture pool".

The heteroskedastic (i.e., dynamic variability), and decreasing ratio between Innovators and Imitators per Bass period is a powerful effect of the Bass diffusion models forecasting. **Firstly, it signals the urgency for retail practitioners to "locate" Innovators quickly in the first or second Bass period of a diffusion scenario**.

If left to later in a reactive "wait-and-see" management style e.g. Christensen asserts that 80% of innovative startup ventures in the US fail because they do not locate and focus on the powerful sustainable profits and revenues available from "Early Adopters" or "Bass Innovators", (Christensen, 2013), the Innovator advantage is wasted. And their ability to positively impact the rate, extent and velocity of the diffusion process; improve sustainable profit and growth and reduce CO2 emissions by buying less - diminishes to little effect by Bass time period 4 or 5.

Knowing the location of REA's can assist in an innovation diffusion "steerage and throttling effect" (Allaway et al., 1994). In other words, Bass model forecasting, period by period, is a guide - if strategic action can engage the retail practitioner with the full numbers of Bass "M" ultimate adopters earlier than forecast by the Bass diffusion model, then this is a highly desirable goal for any innovation diffusion "marketing intervention" operation.

Finally, the ratio of Innovators to Imitators being forecast by the Bass diffusion model both (a) per Bass period and (b) cumulatively; offers opportunities to utilize the ratio of Innovators to measure the likelihood of randomly selecting Adopters (i.e., determining where they are located) as opposed to "Imitators", at all Bass time periods.

Limits, Delimits Ceteris Paribus

The unit of analysis is the "smallest unit of human settlement" (Mason, 1975) and is limited to the decennial "census block".

Only those Census Blocks at each Bass time step "t_x" where the number of potential adopters in a Census Block is greater than zero and are included in the store level trade area shape. The existing Census Block population conjugate priors are delimited to non-children (18+) population statistics. Visualizations are currently limited to inelastic demand for each store location in a monopolistic competitive market. Space or distance is fixed as Euclidean distance only for this study, ceteris paribus. In other words, we specifically delimit distance to be defined as Euclidean (straight line) distance only. There is an important rationale here for using Euclidean as opposed to shortest path or drive time. Unlike shortest path or drive time measurements, Euclidean distance measurements remain unchanged in growing urban landscapes and environments (e.g., changing road networks). More research will extend the addition of drive time and shortest path for possible additional perspectives.

Other delimits include (a) frame the research problem using innovation diffusion theory (b) select/develop an innovative product/service to offer and (c) assumes we see the potential market of adopters as either Innovators or Imitators.

Findings

Can Green-IS with advanced spatial data capabilities (i.e., CyberGIS enabled) and a geospatial information sciences compatible decision support system on the "demand chain" side of the IS hill, be employed to (a) empower a firm to improve its sustainable profits and growth?

The findings show that targeting "pay more, buy less" early adopters support the firm's goal of sustainable profits and economic growth.

Simultaneously, reducing the CO2/Revenue ratio is accomplished because fewer units are purchased at higher prices, thus lowering the quantity of units necessary to be sold.

This can also be analyzed using break even analysis by units or revenue to see the effects clearly.

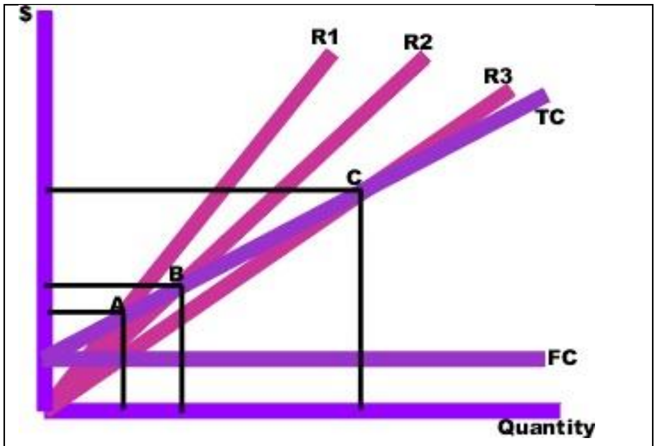

Figure ?. Price/Quantity Correlation

Future Research Opportunities

Studying pricing mechanisms at a much higher granularity than the scope and scale of this paper has allowed, may include the investigation and study of "Dutch-auction" type pricing policies for innovative products minimize CO2/Revenue ratios. More research is need to validate the full range of impacts this approach might allow. The BBSE has been previously validated and likely worthy of further study by innovators e.g., Apple and Tesla for products and services.

Conclusion

Within the limits and delimits od the solution presented, ceteris paribus, the expected results of sustainable profits and growth are achieved. Also the expected reduction in the amount of Co2/Revenue ratio is lower than that of a non-innovative product.

The theoretical model captures empirical evidence of the type of adopters (i.e., WHO), the timing of their potential initial purchases (i.e., WHEN) and most importantly for the "demand chain", marketing function of an organization the likely location of specific adopter types (i.e., WHERE) which allows an organization to efficiently focus resources on very small geographic clusters.

Research like this can meet the goal of exploring potential non-intuitive solutions to the dynamic challenges of global economic actors maintaining sustainable and profitable growth while lowering their environmental impacts (improving environmental sustainability e.g., CO_2 reduction). In other words, "create more economic value for an organization with less environmental impact (e.g., CO_2).

We also conclude from this effort there are new and as yet, untried opportunities to couple sustainability, IS and location into novel and nonintuitive useful permutations.

Green-IS with advanced spatial data capabilities (i.e., CyberGIS enabled) and a geospatial information sciences compatible decision support system on the "demand chain" side of the IS "hill" can empower a firm to improve its sustainable profits and growth.

Reducing the CO_2/Revenue ratio can be accomplished because scientifically selecting certain types of potential customers (i.e., Innovators or Imitators) and effectively and efficiency targeting them to purchase at higher prices (their behavioral characteristic, does lower the quantity of units necessary to be sold to meet sustainable profits and revenues awhile reducing the CO_2/Revenue ratio.

We believe research initiatives like this are needed, across the geospatial information sciences discipline, to cultivate innovative thinking of extensions and new theories to advance the frontiers of integrative applications benefiting from location intelligence. Management science tools like break even analysis can also be deployed in a decision support system.

In the final analysis the following quote speaks to the importance of industry coming up with solutions to the pressing climate change issues and for the rationale to employ more methods and energy in this type of research looking for IS related solutions.

"I think that business is going to have to lead the way in addressing climate change. Governments are pretty much stalled in the effort."

Dr. Steven Moore,

Director - Center for Spatial Studies

University of Redlands

2021

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