A Comprehensive Review of the RMA APH and COMBO Rating Methodology

Final Report

March 15, 2010

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Executive Summary

Sumaria Systems was contracted by the USDA/ Risk Management Agency (RMA) to conduct a comprehensive review of the APH Rating Methodology and the COMBO rating procedure. Our team, including experienced crop insurance analysts and a leading professional actuary, has reviewed the materials provided by RMA and additional materials we collected. Our conclusions are based on the expert opinion of our team and on analysis conducted during the course of our review.

We carefully considered the context of rating crop yield and revenue insurance. The underlying nature of risks insured by crop multi-peril yield and revenue insurance makes these products somewhat unique among property insurance products. First, the products themselves have expanded and changed over time. For example, the introduction of catastrophic coverage and revenue insurance a little over a decade ago has dramatically altered the insurance pool. Further, technological change has occurred rapidly in crop agriculture, yet infrequent but severe weather events are still primary drivers of crop yield insurance losses.

Our review first considered the basic approach taken by RMA in rating the APH and COMBO products. RMA uses historical loss experience as the framework for APH rating and then simulates revenue insurance risk for the COMBO by building from the APH rate and then simulating revenue given price-yield correlations and price volatility. We strongly concur with this mixed approach. The heterogeneous nature of crop yield risk across farms and the variety of perils insured by an APH policy strongly suggest that RMA should use the observed historical loss experience as the foundation for the APH rating system. While alternative simulation-based approaches exist, we conclude that the RMA should avoid such systems as they impose a different and less defensible set of assumptions. We find that the RMA's experience-based approach is typical of property insurance rating.

The approach taken for the COMBO add-ons for revenue coverage in effect 'wraps' revenue coverage around the APH coverage. This allows for rate consistency among the various products. Price volatility is derived from futures options markets and correlations are fairly straightforward to estimate. It is our opinion that this system is fundamentally sound. In general, the nature of price risk is such that very accurate price variability estimates can be obtained from the futures and options markets, and can be applied effectively across a broad set of producers. Thus, the COMBO rating system is designed to make best use of available information.

While we are strongly supportive of the general approach RMA has taken in rating APH and COMBO insurance, we do offer several recommendations for RMA to consider. We have tried to balance consideration of the competing objectives placed on these crop insurance programs and to balance the benefits of the proposed changes relative to the costs to producers, insurance companies, and the USDA. In some cases we believe our

suggestions offer clear improvements to the program. In other cases our review leads us to recommend that the RMA conduct further analysis to evaluate a potential rating improvement.

Basic Approach to APH Rating

We recommend that RMA continue to use loss experience as the foundation of the rating system as it is the only way to assure that actual losses drive the rating results. This is consistent with standard property and casualty insurance rating practices. While crop insurance poses a unique set of actuarial challenges, alternatives to loss-experience-based rating would likely fail to adequately address the multiple objectives of the APH program.

Unit Factor

We recommend that RMA adopt procedures for developing target rates that incorporate unit factors that are consistent with the actual mix of unit structures in the historical loss experience.

Reference Rate, Reference Yield and Exponent

We recommend RMA adopt updated reference yields that are congruent with reference rates and exponents. This is a critical step in obtaining appropriate rates for insured units at all yield levels. These updated reference yields would be based on APH data so that the reference yield and reference rate are 'centered' within a county's book of business. Also, based on our review of the yield ratio curve and the rating exponent, we recommend that RMA conduct analysis to update these parameters of the rating formula.

Type and Practice Factors

We recommend that RMA modify its procedures so that the type/practice factors are applied to the State Catastrophic Rate Load portion of the target rate. Further, we recommend that RMA rebase its rates and type/practice factors to a common type/practice to improve the transparency of the rating structure. We also recommend the RMA adjust prior experience for the current mix of types and practices insured.

Statplan Adjustments

We recommend that RMA eliminate the coverage approximation procedure and adjust all experience to the 50% coverage level when low coverage levels make up a significant proportion of the experience base. We recognize this would place greater reliance on the estimated coverage level relativities. However, we believe these can be effectively estimated for the major crops.

Catastrophic Loading

We recommend that RMA reevaluate the catastrophic loading procedure and reduce the degree to which catastrophic loading influences rates in low risk regions. Having said this, we generally support maintaining state/crop catastrophic loading boundaries, except in the case of a crop with geographically-sparse participation.

Use of Expert Judgment

We recommend that if local conditions have changed such that an existing credible time series of data is not appropriate for rating, an explicit discussion of the changes should accompany a plan to either adjust the prior data or to set a rate through judgment that will then be adjusted using standard methods as new data become available. Regional offices of the RMA should play an important role in this process. The decision and results should be documented, transparent, and reviewable by outside parties.

Additional Rating Variables

We recommend a comprehensive study to evaluate utilizing soil and other site-specific information as factors that could be used to individualize rates. We also suggest RMA consider defining and collecting additional type and practice data for characteristics that likely affect insurance risk levels.

Statewide Rate Level Adequacy

We recommend that RMA evaluate the extent to which statewide rate levels may be inadequate due to capping and, if significant, consider the use of an inadequacy off-balance. We recommend that RMA consider reevaluating whether the minimum catastrophe load is appropriate in light of the disaster reserve factor.

Yield Correlation and Weighting Loss Experience Data

We recommend that RMA evaluate alternative loss cost experience weighting procedures. Our analysis suggests it is feasible to incorporate additional weather information into the rating system and to allow additional weight to be placed on more credible annual observations. However, we do not offer specific recommendations for changing the manner in which experience is weighted over time in current rating methods. We believe a detailed study of this issue should investigate both optimal weights and implementation issues.

Study of Loss Ratio Rating System

We recommend that RMA undertake a comprehensive study of the loss ratio method for determining future rate changes, perhaps in conjunction with a study aimed at a State-level, top-down approach as recommended by Milliman.

Combo Rating

In general we find that the COMBO rating methodology does an appropriate job of combining the various aspects of yield and price risk into a revenue product that provides both a Harvest Price Revenue Rate (HP Rate) and the Harvest Price Exclusion Option Revenue Rate (HPEO Rate). Maintaining consistency between these revenue products and the underlying APH product is not simple. However, we generally concur with the way RMA determines price-yield correlations and price variability. We recommend that RMA consider revising the COMBO rating method to eliminate potential inconsistency in the yield rate relativities applied. Though the differences may be modest in many cases, we believe that a more conceptually sound result would be obtained from applying a consistent set of yield rate relativities across the entire rating process.

Introduction

Sumaria Systems was contracted by the USDA/ Risk Management Agency (RMA) to conduct a comprehensive review of the APH Rating Methodology. RMA designs and rates the Approved Production History (APH) crop yield insurance products which are federally subsidized. Private insurance companies market and deliver these products to U.S. crop producers. These companies are compensated with an administrative and operating reimbursement and provided with reinsurance for their risk exposure.

The APH product provides a yield risk protection guarantee that protects the producer against shortfalls in yield. The yield guarantee is obtained by multiplying the insured unit's APH yield times the coverage level chosen by the producer. If a yield shortfall occurs, losses are valued using a predefined price (value). While various modifications have occurred over time, yield insurance dates back to the inception of the U.S. Multi-peril Crop Insurance Program in 1938.

After this project began, it was modified to also include a rating evaluation of the COMBO policy – a crop insurance product that, in addition to crop yield insurance, also includes a simple revenue (expected price × APH yield) insurance option, as well as revenue upside price protection which bases the guarantee on the higher of the expected or harvest period price. Revenue insurance was first introduced in 1995 and various forms of revenue insurance have been developed. In particular, Revenue Assurance (RA) and Crop Revenue Coverage (CRC) were developed and in some cases provided quite similar coverage. In more recent years, RMA has moved to reduce the redundancy and, with introduction of the COMBO policy, to collapse the revenue products into two variants: revenue insurance and revenue insurance with up-side price protection. The COMBO product in many ways builds upon the yield risk rates of the APH product, which provides the rationale for evaluating the actuarial methodology of the entire COMBO set of products simultaneously.

This report provides the comprehensive review requested by RMA. The Sumaria Systems team approached this project with the intent to provide a detailed, third-party review of the current RMA APH and COMBO rating procedures. In this report we provide an overview of the goals and legislative mandates placed on RMA, describe the RMA procedures, consider alternative procedures, and finally provide recommendations to the Agency. The organization of the report is as follows. In the first chapter we summarize the history of the crop insurance program and provide a background regarding yield and revenue risk. The second chapter provides an overview of the RMA approach to rating the APH product and then Chapter Three provides details of the APH base county rate process. Chapter Four describes mechanisms by which RMA adjusts the base county rate to individual farms in a county. Chapter Five begins our assessment of the RMA rating system by addressing the merits of the RMA system relative to alternatives. Chapter Six addresses suggestions that the review team proposes for rating the APH product. Our review then turns to the COMBO products. Here we review the procedures used and then make suggestions for RMA consideration.

1.0 Crop Insurance Program Background and the Nature of Crop Yield and Revenue Risk

1.1. Brief History of the Crop Insurance Program

The United States Congress first authorized creation of Federal Crop Insurance in the 1930s along with other initiatives to help agriculture recover from the combined effects of the Great Depression and the Dust Bowl. The Federal Crop Insurance Corporation (FCIC) was created in 1938 to carry out the program with three objectives in mind: (a) to protect the income of farmers against crop failure or price collapse; (b) to protect consumers against shortage of food supplies and extreme prices; and (c) to assist business and employment by providing an even flow of farm supplies and establishing stable farm buying power.

In the early years of the program, insurance coverage was limited to major crops (e.g. wheat and cotton) in main producing areas of the U.S. Program participation was low during this period and net losses and loss ratios were high. In fact, losses were so heavy in the early 1940s that the program was discontinued in 1944; but due to political pressure was reintroduced in 1945 (Kramer, 1983; Goodwin and Smith, 1995; Harms, 2005). In 1947, Congress reduced the scope of the program in order to mitigate losses, which prompted the characterization of the program from 1947-1980 as largely being "experimental." During this period participation remained low but loss ratios were much lower than in the early years of the program. Losses were brought under control through the introduction of underwriting and loss adjustment controls. The program also reacted to unfavorable experience by raising premiums, reducing coverage or closing sales.

Passage of the Federal Crop Insurance Act of 1980 marked a transition of the program out of the "experimental" phase into the "modern era" of crop insurance. Developments in the 1980s included expansion of the crop insurance program to cover many more crops and regions of the country and introduction of policy modifications to base coverage on the historical average yield for an insured unit, with individualized rates that decrease as the average yield increases. The 1980 Act also laid the foundation for creation of a public-private partnership between the US government and private insurance companies. Congress expected that the private sector would play a major role in the marketing and delivery of the program to farmers in order to increase participation.

Though the 1980 Act helped expand the program by increasing the number of commodities insured and the coverage provided, farmer participation fell far short of Congress' expectations throughout the 1980s and into the 1990s. In the early 1990s, participation rates were still in the 30% range (significantly below the 50% plus range expected by Congress) and in many years the government provided considerably more in disaster relief expenditures than in crop insurance indemnity payments. Many members of Congress were also frustrated by recurrent requests for ad hoc disaster assistance in the late 1980s and early 1990s that served to undermine the crop insurance program.

Given the situation in the early 1990s, Congress passed the Crop Insurance Reform Act of 1994 that dramatically restructured the program. The 1994 Act made participation in the crop insurance program mandatory for farmers to be eligible for deficiency payments, certain loans, and other farm program benefits. Because participation was effectively mandatory, catastrophic (CAT) coverage was created. CAT coverage compensated farmers for losses exceeding 50 percent of an average yield paid at 60 percent of the price established for the crop for that year. The premium for CAT coverage was fully subsidized. Participants paid a $50 fee per crop per county, subject to maximum amounts for multiple crops and counties insured by the same individual. Farmers could also "buy up" to higher coverage levels offered under the standard multi-peril insurance available at that time.

In 1996, Congress repealed the mandatory participation requirement. However, farmers who accepted certain other benefits were required to purchase crop insurance or otherwise waive their eligibility for any disaster benefits that might be made available for the crop year. These provisions remain in effect today. In the same year (1996), the Risk Management Agency (RMA) was created to administer FCIC programs and other non-insurance-related risk management and education programs for agricultural producers.

The 1994 Act also increased subsidies for insurance coverage levels above the catastrophic level to further encourage participation in the program. By the late 1990s participation rates were approximately double those at the start of the decade. However, despite these increased crop insurance participation rates, supplemental disaster relief legislation was still passed in 1998 and 1999.

Along with the increased subsidies and subsequent growth in participation that has occurred since the 1994 Act, crop insurance has also broadened through the creation of new crop insurance products that are different from the traditional individual yield-based, multi-peril insurance coverage (See Glauber and Collins, 2002). In 1993, an area yield insurance policy called the Group Risk Plan (GRP) was introduced. Under this policy, producers receive indemnity payments based on shortfalls in county average yields rather than individual yields. In 1996 and 1997, the Crop Revenue Coverage (CRC) and Revenue Assurance (RA) policies were introduced. These two products provide coverage for losses based on revenue. A third revenue product called Income Protection (IP) was also introduced in 1996, but this product was piloted on a very limited basis compared to CRC and RA. An area-based revenue insurance design, called the Group Risk Insurance Plan, was introduced in 1999. Note that in 1998, the traditional yield-based insurance product accounted for 82% of insured acres, while CRC and RA accounted for only 14% of the insured acres. By 2008, CRC and RA accounted for 52% of total insured acres, while the APH/MPCI produce only accounted for 22%.

Despite the increase in participation and in the breadth of products offered subsequent to the 1994 Crop Insurance Reform Act, Congress enacted additional legislation in 2000 called the Agricultural Risk Protection Act (ARPA). This legislation increased premium subsidies for coverage levels above CAT and encouraged development of new types of insurance products. ARPA also included provisions designed to reduce fraud, waste, and abuse in the program. In the early 2000s, refinements including continuous rating and variable coverage-level rate differentials were also implemented to better tailor rates to individual farm risks. Additional changes to the crop insurance program were contained in the 2008 Farm Bill, which further encouraged expansion of the program to cover more agricultural commodities (i.e. organic crops, aquaculture, energy crops, etc.) and increased subsidies for insuring at the more aggregate enterprise unit level.[1]

With the increasing number of insurance products being offered and program changes over time, there is a natural concern about maintaining fair and actuarially sound premium rates. As will be described in the sections to follow, the current RMA ratemaking procedure for most individual-level insurance products (e.g. APH, CRC, and RA) relies on historical loss experience data from the program. The advantage of this approach is clear: rates are based on actual loss experience for the program. The disadvantage of this historical loss experience approach is the limited length of time for which historical experience is available as well as the significant program changes that may complicate comparisons over time. Since many crop losses are driven by infrequent but extreme weather events, a 20-30 year time series of loss data may not be sufficient to appropriately reflect loss probabilities (Glauber, 2004). Unfortunately, having a longer experience data base may be problematic due to program changes over time such as increased participation, a shift to revenue products, a shift to higher coverage levels, and rating adjustments made through the years. In addition, underlying yield risks of the crops themselves may evolve and the relative riskiness may not be constant over time – which is suggestive of non-stationary yield risks (Harri et al, 2009).[2] Hence, historical loss experience may not be indicative of future loss expectations given the evolution of changes in the program.

1.2. The Nature of Crop Yield Risks

As touched on above, an understanding of the nature or evolution of yield risks over time is needed so that a particular crop insurance rating approach can be appropriately evaluated. In particular, an understanding of the nature of crop yield distributions is important in order to appreciate the complexity of crop yield risks and, consequently, the difficulty in rating crop yield and revenue insurance products. In this section, we provide a brief description of the crop yield distribution literature that focuses on trends in mean yield, yield variability evolution, the potential influence of climate change on yield risks, and spatial differences in yield risk.

[1] Enterprise units include all of a producer's interest in a crop in a county.
[2] The advantages/disadvantages of the historical loss cost approach and issues related to non-stationary yield risks are discussed in more detail below.

Numerous studies have examined the issue of identifying appropriate crop yield distributions for risk analysis and crop insurance premium rate development (see Norwood et al. 2004; Lu et al., 2008; Harri et al, 2009b for recent studies with brief descriptions of this literature). One consistent thread in this literature has been to recognize that yields in many regions tend to be upward trending over time due to technological advances. Hence, there is general consensus that deterministic yield trends due to technological change have to be taken out prior to risk analysis and insurance rating (Goodwin and Ker, 1998). The typical approach is to first detrend the time series yield data by regressing yields against time and then using the detrended yields for risk analysis and rate making. However, there is no consensus on how to choose the appropriate trend specification and a study by Zhu et al. (2008) even argues that simultaneously estimating the time trend and parameters of the yield distribution may be more appropriate.

In contrast to the widely accepted notion of upward trending mean yields in many crops and regions, there is no general consensus in the literature as to the evolution of yield variability over time.[3] The majority of studies have found a relationship between mean yield and yield variability over time. Many studies, such as those by Hazell (1984), Gallagher (1987), Yang et al., (1992), Traxler (1995), Atwood et al. (2002, 2003), and Harri et al. (2009b), have found evidence of yield heteroskedasticity over time but no strong evidence exists for assuming a constant yield variability over time (see Skees and Reed, 1986; Just and Weninger, 1999). Even though most of the literature has found some relationship between mean yield and yield variability over time, the particular relationship between mean yield and yield variability (i.e. magnitude and signs) significantly varies by region, crop, and practice (among other factors). Furthermore, the nature of this relationship is also strongly influenced by climate and individual farm level risk characteristics.

One important aspect to understanding the nature of crop yield risk is the influence of weather and climate on crop yields. As mentioned in the previous sub-section, crop yield loss events (and consequently yield risks) are driven by extreme but infrequent events. Therefore, a long time-series of yields is needed to adequately represent the true probabilities of yield losses (i.e. the true yield risks). This tends to be an important issue in agricultural risk analysis and crop insurance rating because most yield data sets are not "long" enough to fully characterize crop yield risks. However, consistent with the literature that found non-constant yield variability over time, there are studies that found that yield risks (and yield distributions) are significantly different depending on certain climatic conditions. For example, Ker and McGowan (2000) and Nadolnyak et al. (2008) show that crop yield distributions and risks systematically vary with the different phases of the El Niño Southern Oscillation (ENSO) – a well-known predictor of future weather and climate patterns that can be observed months in advance through oceanic and atmospheric anomalies. A related study by McCarl et al. (2008) showed that crop yield

[3] When there is a relationship between yield variability and mean yield evolution over time (e.g. increasing variability as mean yields increase over time) this is known in econometrics as heteroskedasticity.

variability will generally be higher in the future (2030) based on the climate scenario forecasted by the Hadley and Canadian General Circulation Models (CGMs). This led them to conclude that crop yield variability is not stationary – climate change will increase crop yield variability – and to recommend that risk analysis using historical yield distributions should take this into account. This implies that premium rating procedures that rely on historical yield distributions to set rates for the future may need to incorporate the yield risk-increasing effect of climate change. However it appears that climate change onset would be quite gradual relative to the time period typically used for insurance rating.

Another important issue in understanding the nature of crop yield risk is the spatial heterogeneity of these risks. As touched on above, crop yield risk evolution over time differs by region, crop, and practice. This spatial heterogeneity can be partly explained by the different weather/climate conditions in different regions of the US, but varying resource endowments (i.e. soil quality, topography, etc.) also play a role in the spatial distribution of crop yield risks. The spatial heterogeneity in crop yield risks is evidenced by spatial disparity in loss performance across the different regions of the US (See Glauber, 2004; Babcock, 2008). Generally, the Midwest, California, and parts of the Northwest and Florida have had good loss performance for the period 1981-2003 (loss ratio < 1.0), while the Plains states and the Southeast have had generally poor performance (loss ratio > 1.5) (Glauber, 2004).

2.0 An Overview of the RMA Lost Cost Approach to APH Rates

2.1. Objective of the RMA Actuarial Procedures

As a Federal agency, the USDA/RMA has objectives that differ from those of a private insurance company in which profit in a competitive market is the driving force behind actuarial procedures. In the case of RMA, legislative language found in the Federal Crop Insurance Act contains the following provisions pertinent to rate making:

> *Sec. 508(i) (2) states "Review of rating methodologies. To maximize participation in the Federal crop insurance program and to ensure equity for producers, the Corporation shall periodically review the methodologies employed for rating plans of insurance under this subtitle consistent with section 507(c)(2)."*
>
> *Sec. 508(i) (3) states "Analysis of rating and loss history. The Corporation shall analyze the rating and loss history of approved policies and plans of insurance for agricultural commodities by area."*
>
> *Sec. 508(d) (2) states "the amount of the premium shall be sufficient to cover anticipated losses and a reasonable reserve."*

Thus, RMA is directed to conduct its rating in a manner such that its rates remain actuarially sound. The rates must be sufficient to cover the expected costs, but RMA should not over-price the product such that it drives all but the most risk averse out of the crop insurance market. Further, equity of rates must be taken into consideration. We interpret equity to imply that rates will, to the extent possible, be tailored to be consistent with the risk level of each producer. This implies that loss experience by area is to be evaluated for the purpose of determining whether a sufficient amount of premium will be collected.

Several aspects of Sec. 508 merit note. First, not unlike private insurance there is a balancing of actuarial soundness against program participation. However, this legislation is interpreted to exclude the cost of sales, loss adjustment, underwriting and other activities that a private insurance firm would have to cover. The operating costs of the USDA/RMA are not included in premium rates, nor are administrative and overhead (A&O) reimbursement provided to approved insurance providers (AIP) that deliver the insurance program to producers. RMA rates also do not include a return on investment as would typically be added to a privately-provided insurance product. The reserve provision included in the rates can be compared to a private insurer's provision for profit and contingencies.

Second, we interpret the term "anticipated losses" to imply the mathematical expectations as used in the *Statement of Principles Regarding Property and Casualty Insurance Ratemaking.* There it identifies a fundamental principle of insurance ratemaking as: "A rate is an estimate of the expected value of future costs."

Typically, the largest component of the rate is the provision for losses. While there are other important considerations in rate development, most of the actuarial foundations of ratemaking are intended to provide a framework for estimating the expected loss component of the rate. Because other expenses and costs are provided for in the A&O agreements, the ratemaking procedure deals strictly with deriving the expected loss component. This component is represented by the "loss cost ratio" (LCR), which is derived by dividing expected indemnity by liability. The LCR is a measure of loss per unit of exposure. Thus, one of the objectives of APH ratemaking is to derive LCRs that are representative of the expected losses for a given unit of exposure. If the premium rate is based on an accurately derived expected LCR then the expected loss ratio (indemnity/premium) will equal 1.0. Prior to the Food, Conservation, and Energy Act of 2008, RMA was statutorily mandated to achieve a target loss ratio of 1.075. However, the 2008 Farm Bill lowered that target to the actuarially-fair 1.0 level.

2.2. An Overview of the RMA Actuarial Procedures

Because different crops are subject to different perils and, therefore, varying LCRs, the APH procedure establishes rates for each crop separately. It is rare that a single insured, for any insurance coverage, will have sufficient insurance experience such that expected losses can be estimated solely from the insured's own loss history. In the context of crop yields, ten to fifteen years of experience is often considered an unusually long time-series of available farm-level crop yields. However, as is shown later in this report, that amount of data (i.e. that number of yield observations), is often still inadequate for rating. Thus, it is a common and appropriate insurance practice to aggregate experience of a group of similar risks in developing rates.

For APH, the aggregation is done by crop and geography. Rates are developed by geographic area, primarily at the county level. Thus, for each crop, the APH ratemaking process typically derives LCRs (and consequently rates) by county. There are other determinants used to tailor the rate to an individual producer, depending on utilization of certain farming practices, coverage choices, and rate yield.[4]

[4] The rate yield is the yield upon which the rate for an insured unit is based. In many cases the rate yield is equal to the APH yield for the unit. However, when a substitute yield is used in computing the APH yield or a yield floor is applied the yield used in rating (the rate yield) does not incorporate these substitute yields or yield floor. The rules governing use substitute yields and yield floors can be found in the Crop Insurance Handbook on the RMA web site.

An important consideration as well is that RMA insurance programs are non-discriminatory in that when insurance is offered for a crop in a county it must be broadly available to all producers as long as they do not violate an underwriting provision such as farming in floodplains or using practices not deemed consistent with good management in the area. Thus, producers with little or no yield experience may come into the program. Further, farms in a county may vary dramatically in terms of risk related characteristics such as soil types, slope, production intensity, and irrigation. As a result RMA actuaries are challenged to correctly rate individuals with very little production experience of their own and who may operate in a manner quite dissimilar from nearby producers.

This challenge is also complicated by some of the unique aspects that make crop insurance deviate from standard characteristics of property and casualty insurance. Crop yield risk in most crops and locations is strongly tied to weather variability. The nature of weather is such that there tends to be a relatively high degree of spatial correlation in extreme weather events. For example, a drought may cover an area of hundreds of square miles. Within that region all crops may be affected. This violates the independence of risks that may be observed in lines of insurance such as automobile and life insurance. Weather risk also is quite difficult to accurately assess without many years of observation. This makes it difficult to determine, for example, whether a loss event is a 1-in-100 year event or if it is a 1-in-25 year event. For actuarial purposes this is a critical issue. However, it is not unlike the actuarial challenge confronted by property actuaries rating in hurricane-prone coastal zones.

Another challenge to the APH rating system is the potential for moral hazard and adverse selection to affect losses and rates. These two well-known phenomena are contractual problems arising from asymmetric information between the insurer and the insured. Adverse selection in crop insurance arises when RMA sets rates with incomplete information about the inherent riskiness of the insured and the insured may opt into or out of the program based on better knowledge of his level of risk. This is a common problem in property insurance and is largely addressed by finding observable characteristics of the insured that allow classification of individuals into pools of similar risk. No insurer, private or public, can do this perfectly. But, in the extreme, adverse selection precludes the existence of a private insurance market (Akerlof, 1970). Adverse selection still may be present in the crop insurance program but may be masked by the subsidies applied to the program. As described later in this report, RMA rates vary by a number of observable characteristics of the insured unit. We will assess whether we believe these observed characteristics are sufficient or may be improved.

Moral hazard is a term used to describe an increase in risk-taking behavior due to the producer responding to economic incentives of the insurance contract (Coble et al. 1996). An example would be a crop producer who exerts less effort to protect a crop from insects once insured. In some instances moral hazard implies actionable fraudulent behavior while in other cases it is less clear that moral hazard is anything other than a rational economic response to the terms of the insurance contract. For RMA actuaries, using a historical loss cost approach, moral hazard, if consistent across time and participants, will be captured and built into the rates. The challenge arises when the degree of moral hazard may evolve over time or vary across individuals. One of the most common insurance strategies for reducing moral hazard is the insurance deductible. In the case of APH insurance, the maximum coverage level allowed is 85% which implies a 15% deductible (100% - 85%). Prior to 2000, the maximum coverage level was 75%. The deductible reduces moral hazard incentives as the insured must absorb the value of the first losses incurred. However, price guarantees or APH yields that are set too high can counter the deductible. The problem of moral hazard illustrates why good actuarial analysis must be married with proper policy design (underwriting) for a successful insurance product.

2.3. Overview of the RMA APH Rating Approach

The RMA actuarial process used to generate APH rates primarily uses historical loss experience for a crop in a county to derive the rates for an insured unit within that county. The process begins by collecting the observed insurance and loss data for that county/crop combination and using it to derive a base county rate. The RMA begins by removing or adjusting the individual loss experience to construct the Statplan data, which for most crops, begins in 1975. For example, replanting losses are separated out from the base county rate calculation. Conversely, revenue insurance experience is recomputed as if it were a yield insurance policy to be able to use that data in the base county rate calculation. The objective of this process is to normalize loss experience with various characteristics to a common base. In the next section the process used to derive the base county rate is described.

3.0 Documentation of Procedures for Developing County Base Rates

As indicated above, the RMA rating procedures use historical loss cost experience for a crop in a county in developing county base rates. These county base rates are then adjusted for factors such as coverage level, unit format, crop type, and crop practice to obtain the rate for an insured unit. In this chapter we present a description of the procedures followed in developing county base rates. The summary provided here draws heavily from detailed descriptions contained in an RMA internal document titled "Rate Methodology Handbook: Actual Production History" which is applicable for 2009 and subsequent years. Our objective is to provide a condensed summary of approximately 75% of the information contained in the underlying document, at a level of detail that will allow the reader to understand the RMA's rating process without having to absorb all of the technical and operational details needed for the RMA staff to implement the process. Given that objective, the organizational structure and some of the wording of this chapter closely follows that of large sections of the underlying document. We use quotes where significant passages are taken directly from the Handbook. However, in order to improve the readability of this chapter we do not repeatedly cite the document in the conventional manner. Therefore, this chapter is not represented as original work that does not draw heavily from another source.

3.1. Rate Making Concepts/Methods: Insurance Experience Component

3.1.1. Statplan Database Construction

The Statplan database forms the foundation for the APH rating process. The purpose of Statplan is to provide a reliable database to support sound actuarial decisions. The stated objectives of this database are: "(1) Standardize the multiple policy databases into a single database with multiple years of data under a single standard format, (2) Filter the data to include only data that is relevant to the risk analysis, (3) Stabilize the database so multiple analysts will be evaluating identical historical data, and (4) Summarize the producer experience whereby it is friendlier and provides quicker data access." The steps in Statplan development are:

1. Merge the historical insurance records from 1948 forward to create a simplified database with identical data fields across time.
2. Remove information for policies that are not rated on the basis of actual production history rating procedures.
3. Apply updating procedures that allow reconciliation of computations across time as the underlying insurance experience databases are being continuously updated.
4. Develop data tables containing only the information needed and at the appropriate level of aggregation for rating purposes.

The result of these procedures is the construction of a set of data tables. Two of these tables, the production ratio table and the county summary table, contain the essential data that support the actual production history rating process. The production ratio table contains the data used in computing production ratios, which are discussed in subsequent sections, and the county summary table contains information summarized at the county level and used in evaluating specific risks such as prevented planting.

Below we discuss the treatment of several specific issues in the construction of the Statplan database and its tabular outputs.

Winter Kill Experience

Optional coverage offered for winter wheat and barley poses a challenge in maintaining consistency in the Statplan output tables. These two crops can be planted in either the fall or spring in some regions. In the primary regions where both fall and spring planting are viable production practices, an endorsement with two options (Option A and Option B) is offered. These options provide coverage for losses on fall planted wheat that occur between the fall final planting date and the spring planting date. An additional premium charge is applicable when one of these options is chosen. To maintain data consistency, Statplan separates data for policies choosing this optional coverage from other policies and does not include those data in the computation of production ratios for the crop in the county.

High Risk Experience

The RMA classifies some land as high risk. This includes "acreage with identifiable physical limitations to crop production that may increase the potential frequency and/or severity of losses; or expose a planted or intended crop to perils not generally encountered by most insureds." The RMA states that "such acreage may consist of flood plains, poorly drained areas, high sand content soils, high aluminum toxicity soils, high sodium content soils, high alkali soils, peat soils, soils with high or low pH, soils that are highly erodible, etc." Adjustments are made to base rates for crops planted on high-risk land. Because high-risk experience is not considered to be consistent with other land in a county, this insurance experience is excluded from the production tables upon which base rates are determined and saved in other databases for use in rating high-risk experience.

Whole Farm Units

Most of the insurance coverage based on actual production history procedures is insured at the county/crop level or at a more disaggregated level based on irrigated versus dryland production practices or geographical location of the land. However, the Revenue Assurance product is unique in offering whole farm units which combine the coverage for two or more crops in a county. Insurance experience for whole farm units poses special challenges because this experience cannot be segregated by crop. Therefore, experience based on whole farm coverage is not useful for developing base rates for a crop in a county and is excluded from all Statplan data tables.

Prevented Planting

The RMA defines prevented planting as "a failure to plant the insured crop with proper equipment by the final planting date designated in the Special Provisions for the insured crop in the county." In order to qualify for a prevented planting payment, failure to plant must have been "due to an insured cause of loss that is general in the surrounding area and that prevents other producers from planting acreage with similar characteristics." Prevented planting coverage was first made available for a set of crops insured under the APH insurance design in 1994, with additional crops added later. The amount of base prevented planting coverage differs from 25% to 60% on covered crops with additional coverage options of 5% and 10% on many crops. Prevented planting is not considered a production loss and so prevented planting indemnities and associated liability are excluded from the production ratio tables for a crop in a county. These indemnities and liability are captured in other Statplan databases for use in prevented planting reviews. If planting is prevented on only a part of an insured unit while the remaining acreage is planted, then the experience associated with the planted acreage is included in production ratio tables for use in calculating the county base rate.

Written Agreements

The RMA's definition of a written agreement is: "a document that alters designated terms of a crop policy as authorized under the basic provisions, the crop provisions, or the special provisions for the insured crop." Written agreements are also used to provide coverage for an insurable crop in a county where coverage is not otherwise offered. Insurance experience established under a written agreement is excluded from the standard Statplan rating data because the covered risks are not generally consistent with the risks insured in the county and reflected in published county rates.

Late Planted/Planting Adjustments

The RMA defines late planted acreage as "acreage initially planted to the insured crop after the final planting date designated in the Special Provisions for the insured crop in the county." A late planting period is defined following the final planting date and reduced coverage is offered on acreage that is planted during this late planting period. Thus, the late planting insurance experience is first adjusted to reflect the correct liability/coverage (if it was not late planted) and still included in the Statplan database.

Replants

The RMA defines replanted as: "performing the cultural practices necessary to prepare the land to replace the seed or plants of the damaged or destroyed insured crop and then replanting the seed or plants of the same crop in the insured acreage with the expectation of producing at least the yield used to determine the production guarantee." Thus, replanting occurs when acreage is planted, a viable stand is not obtained, and the acreage is prepared and replanted to the same crop in a timeframe that would not be expected to result in a yield reduction compared with the insured yield. In order for coverage to continue on a crop, the APH based plans of insurance require an insured producer to replant acreage that was damaged prior to the final planting date if the severity of damage is such that: “a majority of growers in the area would not normally further care for the crop…” [Note that this requirement can be waived if the insurance provider agrees that it is not practical to replant.] Indemnities that are paid to insured producers to cover the cost of replanting are not included in the base rate calculations and thus are not stored in the yield ratio or county summary tables. However, the liability and any indemnities paid on replanted acreage are included in the Statplan tables and in base rate development because the acreage is planted under conditions that are expected to produce at least the guaranteed yield.

Revenue Adjustments

Three revenue insurance products were introduced by the RMA in the mid 1990s. Two of these plans of insurance, Revenue Assurance (RA) and Crop Revenue Coverage (CRC), were privately developed and submitted for approval by the Board of Directors of the FCIC. The third product, Income Protection (IP), was developed by the RMA. All of these products insure producers against shortfalls of gross revenue below a guaranteed level and in all three the yield risk component of the coverage is based on APH procedures. The expected or base price used in determining the revenue guarantee is established using futures market prices for a harvest-period contract during a specified set of days in the weeks prior to the sales closing date. Harvest period prices for the same futures market contract at harvest time are used in determining the value of production to count and in calculating indemnities.

These three plans of insurance are similar but not identical. Some differences are:

- CRC bases the insurance guarantee on the higher of the base price or the harvest period price.
- IP and standard RA guarantees are determined using the base price, with no adjustment in coverage if the price increases between the times when the base and harvest prices are established.
- RA offers up-side price protection like that of CRC as an option but IP does not.
- IP limits unit formats to basic units, which include all interest in a crop in a county held under identical ownership.
- RA is unique in offering coverage on whole farm units, which integrates the coverage on from two to three crops.

Because these revenue plans of insurance (especially CRC and RA) have grown in popularity and now account for a large proportion of coverage for some crops, it is essential to use the experience associated with these products in setting the actual production history rates. The RMA states that in order to do this “revenue adjustments must occur and are accomplished in an automated routine by converting these records to equivalent APH records for use in APH rate evaluations.”[5] The adjusted data are included

[5] IP experience is not used in deriving actual production history rates because the product uses a separate yield rating process and offers only enterprise units.

in Statplan, with identifiers for the insurance plan. The following are the Statplan adjustments to revenue product liability and indemnity as described in the "Rate Methodology Handbook: Actual Production History" discussed earlier.

Liability Adjustment:

$$StatPlan\ Liability = Revenue\ Liability \times \frac{APH\ Price\ Election}{Revenue\ Based\ Price}\ .$$

Indemnity Adjustments:

Step 1A: $Loss\ Guarantee = Revenue\ Liability$

Step 1B: $Loss\ Guarantee = Revenue\ Liability \times \frac{Max(Base\ Price, Harvest\ Price)}{Base\ Price}$

Step 2:

$$Production\ to\ Count\ (PTC) = Loss\ Guarantee - Revenue\ Indemnity$$

Step 3: $Indemnity = StatPlan\ Liability - \left[PTC \times \frac{APH\ Price\ Election}{Revenue\ Harvest\ Price}\right]$

Step 4: $StatPlan\ Indemnity = Max(Indemnity, 0)$

What the above calculations do is transform indemnities for revenue insurance products to be equal to what they would have been if the coverage were based on the fixed APH Price Election rather than the revenue plan base price and harvest price. The result is a calculated indemnity, *for insured units that are indemnified*, that is equal to what the indemnity would have been under APH yield insurance. This achieves consistency within the Statplan data across the APH yield insurance product, CRC and RA, with or without a harvest price feature or option.

Revenue Adjustments for Replanted Acreage

The process described in the previous section is used to convert revenue product loss experience to equivalent yield losses. A similar process is followed for replant losses. The liability conversion is the same as described earlier and remains in the production ratio tables. The formula used in converting replant indemnities on revenue products to yield equivalents in Statplan is as follows:

$$StatPlan\ Rplt\ Indemnity = Revenue\ Rplt\ Indemnity \times \frac{APH\ Price\ Election}{Revenue\ Base\ Price}\ .$$

Production Ratio Calculations

The "Rate Methodology Handbook: Actual Production History" uses the following set of mathematical expressions to define the production ratio.

$$Production\ to\ Count\ (PTC) = Liability - Indemnity$$

$$Liability = Expected\ Production \times Coverage\ Level$$

which implies,

$$Expected\ Production = Liability/Coverage\ Level\ .$$

The production ratio is defined as:

$$Production\ Ratio\ (PR) = \frac{Production\ to\ Count}{Expected\ Production}$$

which, following from above, can be computed as:

$$Production\ Ratio\ (PR) = \frac{PTC}{Liability} \times Coverage\ Level\ .$$

The minimum production ratio of zero is associated with no production to count on an insured unit. The maximum computed production ratio is equal to the coverage level. For example, if expected production per acre (in dollars) is $100 and the 75% coverage level is selected then an indemnity is recorded only if the value of production per acre, based on the APH price election, is below $75 per acre. Thus, the maximum computed production ratio approaches $0.75 = 75/100$. This maximum production ratio also is assigned to all cases where production to count exceeds liability and thus is not recorded because no loss is reported.

3.1.2. Statplan Database Construction: Liability and Indemnity Adjustments

The section of the internal RMA report "Rate Methodology Handbook: Actual Production History" summarized in this section contains detailed descriptions of the structure of the Statplan database. The summary of that information provided here is limited. Presumably, anyone who is given access to the Statplan database will also have the "Handbook" available for reference. Without access to the Statplan database, the database descriptions contained in the "Handbook" are of limited value except in understanding how the data support the rating process and in evaluating changes in the database that would be required to support proposed modifications to the rating methods. Here we describe the information in the database only to the extent necessary to explain the rating process.

Historically, the RMA's rating process has involved development of target and base rates at the county/crop level. A fundamental step in this process is summarizing loss experience for each year in the historical rating period across all relevant insurance plans, crop types, crop practices, and coverage levels. Liability and indemnity for revenue insurance plans are converted to a yield basis as described above. A second critical step in the rating process is converting the experience for a crop in a county to a common coverage level. The common coverage level used as the base for APH rating is the 65% coverage level. Therefore, loss experience for units insured at levels above 65% must be adjusted down to reflect what it would have been at the 65% coverage level and loss experience for coverage levels below 65% must be adjusted upward to what it would have been at the 65% coverage level. Here we describe the process used by the RMA in making these coverage level adjustments. In doing so, we rely heavily upon examples provided in the "Rate Methodology Handbook: Actual Production History".

Adjustments to Liability

Tables 3.1 and 3.2 show simplified examples of 70% and 60% insurance experience for a crop in a county. For each recorded production ratio, these tables show the following information: discrete indemnity, discrete liability, cumulative indemnity, and cumulative liability. Discrete indemnity and discrete liability are the amounts of indemnity and liability on insured units that have the indicated production ratio. For example, Table 3.1 shows that insured units with a production ratio of 0.62 accounted for $4,540 in indemnities and $40,076 in liability, when insured at the 70% coverage level. Cumulative indemnity and cumulative liability are the amounts of indemnity and liability on insured units that have recorded production ratios at the indicated level *or below*. For example, Table 3.1 shows that insured units with a production ratio of 0.62 or below accounted for $567,310 in indemnities and $1,515,350 in liability. It should be noted that for convenience Table 3.1 does not display information for production ratios less than 0.60. However, this production experience is reflected in the cumulative indemnity and cumulative liability amounts. Also, since the maximum production ratio of 0.70 is recorded for all cases where production to count exceeds liability, discrete liability recorded at a production ratio of 0.70 includes liability for that production ratio and all non-observable production ratios above that level. Cumulative liability recorded at a production ratio of 0.70 includes liability for that production ratio, for production ratios below that level and for all non-observable production ratios above that level.

Adjusting liability from higher or lower coverage levels to the common coverage level of 65% is straightforward. All that is required is multiplication of total (cumulative) liability at the actual coverage level by the ratio of the common coverage level to the actual coverage level. For example, Table 3.1 shows cumulative liability of $4,681,802 at the 0.70 production ratio. This is the total liability insured at the 70% coverage level. This liability is multiplied by the ratio 65/70 to obtain liability of $4,347,388 at the 65% common coverage level. Table 3.2 shows cumulative liability of $41,418 at the 60% coverage level. This is multiplied by the ratio 65/60 to obtain liability of $44,870 at the 65% common coverage level.

Table 3.1. Example Loss Experience at the 70% Coverage Level

Coverage Level
70 Percent

Production Ratio	Discrete Indem	Discrete Liability	Cumulative Indem	Cumulative Liability
0.60	6146	41951	552681	1397956
0.61	10089	77318	562770	1475274
0.62	4540	40076	567310	1515350
0.63	630	6584	567940	1521934
0.64	2465	30436	570405	1552370
➔ **0.65**	481	6320	➔ **570886**	➔ **1558690**
0.66	188	3641	571074	1562331
0.67	1061	27527	572135	1589858
0.68	1144	37072	573279	1626930
0.69	875	46935	574154	1673865
0.70	49	3007937	574203	4681802

Table 3.2. Example Loss Experience at the 60% Coverage Level

Coverage Level
60 Percent

Production Ratio	Discrete Indem	Discrete Liability	Cumulative Indem	Cumulative Liability
0.04	2330	2516	2330	2516
0.25	5083	8812	7413	11328
0.37	1530	4069	8943	15397
0.47	854	3978	9797	19375
0.58	174	4293	9971	23668
0.60	0	17750	9971	41418

Adjustments to Indemnities

The process of adjusting indemnities to a common coverage level depends on whether the actual coverage level is higher or lower than the common coverage level. Here we explain each of these cases.

Case 1 – Adjusting higher coverage levels down to the common coverage level

The process of adjusting indemnities for higher coverage levels to the common coverage level is straightforward. Here we use the information in Table 3.1 to illustrate this process. At the 65% common coverage level, indemnities are paid only if the production ratio is 0.65 (with rounding) or below. Therefore, recorded indemnities for production ratios above 0.65 can be ignored. The adjustment of indemnities in this case is described by the RMA as the following five step process using the information in Table 3.1.

Step 1: Cumulative Indemnity ($I_{@65}$) = \$570,886

Step 2: Cumulative Liability ($L_{@65}$) = \$1,558,690

Step 3: Cumulative Liability re-stated at 65% (L_{65}) = $L_{@65} \times 65/70$

= \$1,447,355

Step 4: Reduction in Liability = $L_{@65} – L_{65}$ = \$1,558,690 - \$1,447,355

= \$111,335

Step 5: Adjusted Indemnity (I_{65}) = $I_{@65}$ – Reduction in Liability

= \$570,886 - \$111,335

= \$459,551

Steps 1 and 2 are just a statement of cumulative indemnities and cumulative liability at a production ratio of 0.65 (associated with the 65% common coverage level). Step 3 converts the 70% coverage level cumulative liability at a production ratio of 0.65 to what that liability would be at the 65% common coverage level. In step 4, the reduction in 0.65 production ratio cumulative liability resulting from conversion from the 70% to 65% coverage level is computed. In step 5 the adjusted 65% coverage level indemnity is computed by subtracting the reduction in liability (Step 4) from 0.65 production ratio cumulative indemnities (for the 70% coverage level) from step 1.

Case 2 – Adjusting lower coverage levels up to the common coverage level

The process of adjusting indemnities for lower coverage levels to the common coverage level is complicated by the fact that detailed information on indemnities and liability for production ratios between the actual coverage level and the common coverage level is not available. Here we use the information in Table 3.2 to illustrate the process RMA follows in making these adjustments.

A lower bound for the estimate of indemnities at the 65% common coverage level can be calculated as follows.

$$\text{Min } I_{65} = [L_{<60} \times {}^{65}/_{60}] - L_{<60} + I_{60}$$

$$\text{Min } I_{65} = [\$23{,}668 \times {}^{65}/_{60}] - \$23{,}668 + \$9{,}971$$

$$\text{Min } I_{65} = \$1{,}972.33 + \$9{,}971$$

$$\text{Min } I_{65} = \$11{,}943$$

Here, $L_{<60}$ is cumulative liability for the highest recorded production ratio that is *less than* the actual coverage level (in our example from Table 3.2 a production ratio of 0.58). This is multiplied by the ratio of the common coverage level to the actual coverage level to obtain the liability for policies with production ratios less than the actual coverage level, when adjusted to the 65% common coverage level. The actual cumulative liability ($L<60$) is subtracted from this to obtain the change in liability associated with insuring at the 65% common coverage level versus the actual coverage level of 60%. This change in liability is added to the cumulative indemnity at the 60% coverage level to obtain the lower-bound or minimum indemnity at the 65% coverage level. Note that this lower-bound or minimum estimate of indemnities at the common coverage would accurately reflect indemnities at this coverage level if there were no (non-observable) indemnities at production ratios between 0.60 and 0.65.

An upper bound for the estimate of indemnities at the 65% common coverage level can be calculated as follows.

$$\text{Max } I_{65} = [L_{60} \times {}^{65}/_{60}] - L_{60} + I_{60}$$

$$\text{Max } I_{65} = [\$41{,}418 \times {}^{65}/_{60}] - \$41{,}418 + \$9{,}971$$

$$\text{Max } I_{65} = \$3{,}451.50 + \$9{,}971$$

$$\text{Max } I_{65} = \$13{,}423$$

In this case it is important to recognize that L_{60} is total insured liability (including that associated with production ratios below, at, or above the 60% coverage level). Multiplying this by the ratio of the common coverage level to the actual coverage level (65/60) obtains total liability at the common coverage level. Subtracting cumulative liability at the 60% coverage level (L_{60}) obtains the change in total liability if all units had been insured at the 65% common coverage level rather than the actual 60% coverage level. Adding this change in total liability to cumulative indemnities at the 60% coverage level (I_{60}) provides the maximum indemnity that could have resulted at the common 65% coverage level. Note that the implicit assumption underlying this calculation process is that all policies have production ratios less than the common coverage level. If this were true then this would be an exact conversion of indemnities from the 60% to 65% common coverage level. However, if some policies have production ratios greater than the common coverage level, then this process over estimates indemnities at the 65% common coverage level.

The adjusted indemnity estimate is obtained as follows.

$$I_{65} = MinI_{65} + [(L_{60} - L_{<60}) \times (65/60) - (L_{60} - L_{<60})] \times (I_{60} / L_{60})$$

I_{65} = \$11,943 + [((\$41,418 - \$23,668) x (65/60)) – (\$41,418 - \$23,668)] x (\$9,971/\$41,418)

I_{65} = \$11,943 + [\$1,479 x 0.24074]

I_{65} = \$11,943 + \$356

I_{65} = \$12,299

The first term in this expression ($MinI_{65}$) is the lower-bound or minimum indemnity calculated above. Remember that this indemnity estimate made adjustments for policies with production ratios less than the actual coverage level and no adjustments for policies with production ratios at or above the actual coverage level. The remainder of the expression estimates the indemnity adjustment for policies with production ratios at or above the actual coverage level. We believe this is best understood when the part of the expression to the right of $MinI_{65}$ is rewritten as follows.

$$[(L_{60} - L_{<60}) \times (65/60) - (L_{60} - L_{<60})] \times (I_{60}/L_{60})$$

$$= \frac{[(L_{60} - L_{<60}) \times ((65/60) - 1))]}{L_{60}} \times I_{60}$$

The first term in the numerator of the fraction above is total liability at or above the 60% coverage level. This is multiplied by the adjustment factor $((65/60) - 1)$for the difference in 60% coverage level liability and 65% coverage level liability. Thus, the numerator is the difference between 60% coverage level liability and 65% common coverage level liability for policies that are not accounted for in the minimum indemnity adjustment $MinI_{65}$. This is divided by total 60% coverage level liability (L_{60}) to obtain the percentage change in total liability when liability for 60% or higher production ratios is converted from the 60% coverage level to the 65% coverage level. This percentage change in total liability is multiplied by total 60% coverage level indemnities and then, as indicated above, added to $MinI_{65}$ to obtain the adjusted indemnity estimate. What this process does is to directly compute the change in indemnity for units with production ratios below the actual coverage level, estimate the change in indemnity on units with production ratios at or above the actual coverage level, and sum the two to get the adjusted indemnity. The assumption underlying the estimate for policies with production ratios above the actual coverage level is that the percentage change in indemnity is equal to the computable percentage change in liability.

3.2. Rate Making Concepts/Methods: Reference Yield Component

The RMA introduced the APH plan of insurance for corn, grain sorghum, peanuts and tobacco in 1986. Subsequently, individual yield coverage for a large number of crops, as well as the related CRC and RA revenue insurance products, have incorporated this basic product design. The RMA has identified two distinguishing features of this insurance product design: "1) the growers guarantee was based on their actual production history (APH) [and], 2) the growers premium rate was based on their actual production history (APH yield) relative to other growers in the same geographic area." The latter relationship, between grower and regional yield, is a function of the ratio $y_i/\bar{y}$, where y_i is the grower's APH yield and $\bar{y}$ is intended to represent the "center point of the yield range" for growers of the same crop type and practice in the rating area. This is referred to as the reference yield for the crop type and practice in the area. As will be seen in the next chapter, the reference yield plays an important role in determining the premium rate for an insured unit. Since 1986, a number of methods have been used to calculate and update reference yields. Currently, target reference yields are established using the following procedures as laid out in the "Rate Methodology Handbook: Actual Production History."

1. The transitional yield (t-yield) is multiplied by two factors to create limits of movement.
2. If the reference yield was within the boundaries calculated in step 1, no change was made to the reference yield.
3. If the reference yield was outside the boundaries calculated in step 1, the reference yield was updated to equal the t-yield boundary.

Thus, when updated, target reference yields for a crop are calibrated to be within a specified range of the t-yield for the crop.[6]

3.3. Rate Making Concepts/Methods: Coverage Level Rate Relativity Component

Because of program changes over time, coverage levels available to producers have expanded dramatically over the loss experience used in rating by RMA. Prior to 1980 only one coverage level was available – 65% coverage. The Federal Crop Insurance Act of 1980 added two additional coverage levels at 50% and 75% coverage. At that time RMA developed coverage level differentials that adjusted rates from the base 65% coverage to the other two coverage levels. By 1985, these relativities were largely fixed across crops and regions with 65% coverage rates set at 65% of the 75% coverage rate and the 50% coverage rate set to 47% of the 75% coverage rate.

The 1996 Federal Agricultural Improvement and Reform (FAIR) Act modified crop insurance by specifying coverage levels would be offered from 50% to 75% coverage in 5% increments. Then in 1998, 80% and 85% coverage levels were added for selected crops and regions. With these additions rate relativities were set as:

Table 3.3. Fixed Coverage Relativities Used Prior to the Current Variable Relativity Approach

Coverage Level	Rate Relativity
85%	1.60
80%	1.22
75%	1.00
70%	0.79
65%	0.65
60%	0.51
55%	0.47

Beginning in 1996 several crop revenue products were introduced. These new products were rated with alternative methodologies. As these products became increasingly popular differences in the way the alternative rating methodologies handled coverage relativities became obvious. This led RMA to reevaluate coverage level relativities. Through a series of studies beginning in 2002, RMA began implementing variable coverage relativities that are conditioned on the riskiness of the crop and endogenous risk factors that account for behavioral changes as the coverage level increases (deductible decreases). More detail on this process is provided in section 4.5.

[6] Transitional Yield (or t-yield) is defined as "An estimated yield provided in the Actuarial Table which is used in calculating average/approved APH yields when less than four years of actual, temporary, and/or assigned yields are available on a crop by county basis" (2007 Crop Insurance Handbook, p. 16). For additional information on Transitional Yields see Section 6E of the 2007 Crop Insurance Handbook.

3.4 Target Rate Development Component

Once RMA has adjusted existing loss experience in the Statplan data development process, the actuarial branch begins a multi-step process to develop a target rate for a county/crop program. In effect, the target rate is the rate RMA believes should serve as the base upon which rates in a county are anchored.

3.4.1 Capped Loss Cost

RMA uses a catastrophic loading procedure to reduce the influence of outliers in the experience of a county/crop program. Because crop losses are often characterized by infrequent but severe losses, even several decades of county loss experience may be subject to sampling error. Catastrophic loading is an actuarial technique to mitigate the effect of sampling error when the true magnitude of sampling error is not known. Catastrophic loading is intended to remove anomalous experience from the county/crop data but not remove normal loss experience. In general, losses deemed catastrophic are spread across all counties for a crop in a state. Thus, the capping of loss cost experience in a county/crop program is not a load in the sense that it is an additional factor added to rates, but rather it redistributes loss experience within a state/crop program.

The current RMA procedure censors the county loss experience at the 80th percentile of the historical county experience. No distributional assumptions are required for the procedure. To illustrate this, assume 30 years of data are available for the county/crop program. Then the 80th percentile of the loss cost is the 24th highest observed loss cost ratio (note when the percentile does not fall on a discrete observation, a linear interpolation is used).

All observations with indemnities above the truncation point are aggregated to the state/crop program level. For a county, the catastrophic (CAT) indemnity is calculated as follows:

$$CAT\ Indemnity = \left[\frac{Adjusted\ Indemnity}{Adjusted\ Liability} - Capped\ LCR\right] \times Adjusted\ liability$$

The CAT indemnities are used in the catastrophic loading calculations described below and losses not removed into the cat indemnity are used in the calculating the county unloaded rate.

3.4.2 Net Acres Insured

RMA uses credibility weighting to smooth rates among adjoining counties. Credibility in the RMA process is a function of net acres insured so a historical record of net acres insured is retained in the Statplan process.

3.4.3 County Unloaded Rate Determination

The county unloaded rate is a weighted combination of the county LCR after removal of the catastrophic (CAT) indemnity and the LCR of surrounding counties. Both LCRs are calculated after removal of the CAT indemnity. For many years RMA used weights of 60% for the target county and 40% for the circle LCR. Milliman USA recommended refinements of this process that were adopted in 2006 which replaced the historical weights with a procedure which credibility weights the target county and surrounding counties based on a function of the acres underlying the target county's data and the circle's data. RMA now refers to the surrounding counties as the county group or credibility complement. A surrounding county is defined to be a county which corners or borders the target county. The exact process used by RMA follows a decision tree as follows:

Step 1:

Does the target county have at least six consecutive most recent years of data, at least 5 exposure units, and at least one non-zero indemnity observation after applying capping?

If the answer is yes, calculate the credibility weight using the Bühlmann method.

If the answer is no, then ask;

Step 2:

Does the county group have at least six consecutive most recent years of data, at least 5 exposure units, and at least one non-zero indemnity observation after applying capping?

If the answer is yes then rate the target county using 0% credibility.

If the answer is no rate the county subjectively.

The following outlines the procedure for calculating the target rate using the Bühlmann weights:

$$R = ZX + (1 - Z)\mu$$

$$\text{where: } Z = \frac{P}{P + K}$$

The variables in this equation are defined as:

R = County Unloaded Target Rate
Z = Bühlmann credibility factor, ranging from 0 to 1
X = The sample mean of an individual county to which credibility is applied (average of the adjusted capped LCRs for all available years of data for the county)
μ = The underlying mean (average of the adjusted capped LCRs for all available years of data for the entire *county group*)
P = Exposure units (Total number of net acres for a given crop in the target county summed over all available crop years divided by the appropriate α)
$K = v/a$ where: v = Sample variance of the adjusted capped LCRs for all available years of data for the target county; and a = Sample variance of the Xs from the county group

The target rate is a weighted average of the county's capped experience (X in the formula) and the experience of the county group as a whole (μ). A county's "credibility" (Z) increases with the exposure underlying a county's experience (P). It also increases if the variance in the year-to-year experience for the county (v) is low and/or if there is a lot of variance in the average experience among the counties in the county group (a). Thus credibility weighting adds additional information from the surrounding counties in cases where the individual county's experience is either sparse (few exposure units) or highly variable. It also serves as a smoothing mechanism which reduces discrepancies between the rates of adjoining counties.

3.4.4 State Catastrophic Load

Given the county CAT indemnities described in section 3.4.1, the state CAT load for a crop is calculated as:

$$State\ CAT\ Load = \frac{\sum County\ CAT\ Indemnities}{\sum Liability\ of\ all\ counties}$$

However the state CAT load is limited to a maximum of .0325 and a minimum of .0065 for all states and crops.

3.4.5 County Catastrophic Load

Because the state CAT load is capped at 0.0325 some state/crop programs have a county CAT load that reallocates any state excess above the 0.0325 cap back to each county proportional to each county's adjusted liability. The purpose for the caps is to limit the amount of rate being shared across all counties when the counties may or may not be homogenous. Because the state CAT loading, up to 0.0325, is applied evenly to all counties regardless of the county's indicated unloaded target rate, the state CAT load represents a larger proportion of the total rate in counties with better experience.

If the state CAT load is greater than 0.0325, the following calculations are performed to establish the target county's County Cat Load.

$$Target\ county\ Indemnity\ Portion = \frac{\sum Target\ county\ CAT\ indemnity}{\sum State\ CAT\ Indemnity}$$

$$Excess\ State\ Indemnity = excess\ state\ CAT\ load\ \times state\ adjusted\ liability$$

Then

$$Target\ County\ Liability = \sum target\ county\ adjusted\ laibility$$

Finally

$$Target\ County\ CAT\ Load = \frac{Target\ County\ Indemnity\ Proportion \times Excess\ State\ indmenity}{Target\ County\ Liability}$$

Note this procedure spreads indemnities in proportion to the counties' contribution to the total CAT indemnity (including the non-excess portion). Thus, counties with more CAT losses receive a relatively greater portion of the load for excess catastrophe losses (if there is one).

3.4.6 Miscellaneous Rate Loads

As noted earlier losses due to certain causes are removed from the Statplan data and treated separately. There are three rate loads incorporated in the ratemaking process: 1) Prevented Planting rate load; 2) Replant rate load; and 3) Quality Adjustment rate load. However, not all crop policies include these coverage options. These rate loads are associated with losses that are in some fashion less directly related to yield loss. In the case of prevented planting the crop is never seeded. In the case of replant coverage one is really covered against the additional cost incurred to replant the crop. Quality losses reflect a reduced crop value rather than production. Also, some of the coverage options have been offered for a limited period. Prevented planting coverage was first offered for a limited set of crops in 1994. Quality adjustment language was added to a number of crop policies beginning with spring crops of crop year 2000. The procedures used to develop these loads are not well defined due to the inability to accurately identify quality losses in RMA data and the limited experience in other cases.

3.4.7 Disaster Reserve Factor

Legislative mandates require RMA to set rates that "cover anticipated losses and a reasonable reserve." The disaster reserve is intended to meet the reasonable reserve requirement of the program. RMA's current disaster reserve factor is 0.88 for all crops and insurance plans. This factor is incorporated into rates by dividing the unloaded county rate and the county CAT load by 0.88. This results in a 13.6% increase in this portion of rates. RMA recently contracted with an outside actuarial firm to review the adequacy of the disaster reserve factor load. Based on that review, RMA has continued to use the 0.88 disaster reserve factor.

3.4.8 Optional Unit Factor

Various aggregations of crop acreage are allowed in the APH program – optional, basic, enterprise, and whole-farm units. Spatial aggregation of crop acreage will have the tendency to reduce risk as less than perfectly positive correlation is typically observed. The data for Statplan rating are a mixture of these unit structures. However loss experience prior to 2009 is dominated by basic and optional unit experience. The 2008 Farm Bill resulted in a change in subsidy that encourages enterprise unit coverage. Thus, future experience may include more of this experience.

The basic unit structure is the reference unit format for rating. RMA loads the historical optional unit experience by the discount for selecting basic units over optional units. For many years the multiplicative discount factor for basic units has been set at 10%. RMA recently contracted for an external review of the appropriate discount and unit structure. The study concluded that the current unit structure does not need to be changed. However, the current basic unit discount of 10% could be improved by tailoring it to vary across crops, regions, and unit structures (including enterprise units). The FCIC Board has approved adoption of the study recommendations. RMA planned to implement the variable unit discount but implementation has been suspended while awaiting the RMA's eWA system redesign. More details of unit rate adjustments are provided in section 4.6.

3.4.9 County Target Rate

The county target rates bring together the various computations discussed in this chapter. In general there are two primary components of the county target rate: 1) the variable rate portion and 2) the fixed rate portion. The distinction is that the variable rate portions can differ based on the insured unit's approved yield while the fixed portion of the rate remains constant across all approved yields. In chapter 4, the formulas and process by which rates are quoted for a particular unit given the county target rate will be described in detail.

3.4.10 Judgment Target Rate

The formula-driven rating process described in this chapter is applied to thousands of county/crop programs. To maintain rating accuracy, RMA conducts a review of and sometimes intervenes in setting the rates. This is most likely in cases where county experience is limited or the county experience does not reflect expected yields. This is most likely when county data lack credibility. County target rates that are judged to be not credible undergo a mandatory review by the AB and Regional Underwriting Office.

3.5. Mandated Capping Requirements Component

By legislative mandate, RMA rate changes are capped at 20% compared to what the insured would have paid the previous year for the same coverage. However, premium decreases can exceed 20% to allow the base rate to reach the target base premium rate within three years. To summarize the capping procedure, consider first the formula of the Base Producer Rate (BPR).

$$BPR = \left(\left(\frac{APH\ Yield}{Reference\ Yield}\right)^{Exp} \times reference\ rate + fixed\ load\right) \times \begin{matrix} Coverage \\ Differential \end{matrix}$$

Note that ratio of APH yield to the reference yield is bounded between 0.5 and 1.5. To assess the rate change RMA compares two producer rates – an initial rate and a target rate. Four factors may induce a rate change in this calculation: 1) the reference yield, 2) reference rate, 3) fixed loads, and 4) coverage differential. The total effects of these factors are compared through the calculation of these two equations.

$$BPR_{Int} = \left(\left(\frac{APH\ Yield}{Reference\ Yield_{int}}\right)^{Exp} \times reference\ rate_{int} + fixed\ load_{int}\right) \times \begin{matrix} Coverage \\ Differential_{int} \end{matrix}$$

$$BPR_{Tgt} = \left(\left(\frac{APH\ Yield}{Reference\ Yield_{Tgt}}\right)^{Exp} \times reference\ rate_{Tgt} + fixed\ load_{Tgt}\right) \times \begin{matrix} Coverage \\ Differential_{Tgt} \end{matrix}$$

Where the subscript "Int" reflects the base period value and the subscript "Tgt" indicates the target value. Caps on rate changes are then applied using the following equations.

If $BPR_{Tgt} > BPR_{Int}$ then

$$BPR_{Capped} = Min\left[BPR_{Tgt,} Min\left((1.09 + 0.06 \times \Delta BPR_{65}) \times BPR_{Int}\right), 1.2 \times BPR_{Int}\right]$$

Where ΔBRP_{65} is the percent change in the base premium rate at the 65% coverage level.

If $BPR_{Tgt} < BPR_{Int}$ and BPR_{Tgt} will be reached in three years then:

$$BPR_{Capped} = BPR_{Int} \times Max\left(0.91 - 0.06\left(\frac{BPR_{Int}}{BPR_{Tgt}} - 1\right), 0.8, \frac{BPR_{Tgt}}{BPR_{Int}}\right)$$

If $BPR_{Tgt} < BPR_{Int}$ and BPR_{Tgt} will not be reached in three years then

$$BPR_{Capped} = 1.23 \times BPR_{Tgt}$$

3.6. APH Business Process and Critical Control Component

RMA produces rates for several thousand county/crop programs each year. In many cases there are multiple insurance designs for a particular county/crop program. To maintain quality, RMA defines a strict filing schedule and maintains critical control points as well. Specifically, there are a series of reviews and multiple inspections. RMA's actuarial branch periodically reviews and updates documented support for all factors in the rate determination process. Typically rating factors are reviewed every 3 years unless the underlying study suggests a longer interval for review.

4.0 Adjustments from County-Level Target Rates to Individual Rates

4.1. Introduction

The discussion in the previous sections describes the process by which target rates at the crop/county level are derived. At the county level and without adjusting for crop type and cropping practice, target rates can be characterized as follows:

$$\text{(Eq. 4.1)} \qquad \text{Target Rate} = \left(\frac{\left(\frac{\text{ULR}+\text{CntyCAT}}{\text{ResFac}} \right)}{\text{UnitFac}} \right) + \left(\frac{\text{PP}+\text{RP}+\text{QA}+\text{StCAT}}{\text{UnitFac}} \right)$$

where: ULR = County Unloaded Rate, CntyCAT = County Catastrophic Rate Load, ResFac = Disaster Reserve Factor (0.88), PP = Prevented Planting Rate Load, RP = Replant Rate Load, QA = Quality Adjustment Rate Load, StCAT = State Catastrophic Rate Load, and UnitFac = Unit Division Factor (here a factor of 0.90 is used).

In order to "individualize" the target rate above, the county unloaded rate (ULR) is first multiplied by the yield ratio (Ry) raised to a negative exponent (-E). The yield ratio is defined as the ratio of an individual farmer's rate yield to the reference yield for the crop type and practice in the county (Ry= individual rate yield/reference yield). The rate is further "individualized" to the particular crop type and practice of the farmer by multiplying the left hand term by a type/practice factor (TpFactor). Lastly, the individual producer's choice of coverage level is taken into account by utilizing a coverage level differential (CLD) and the rate is adjusted by the appropriate unit structure factor (UnitFac). The preceding adjustments can be expressed as follows:

(Eq. 4.2) Target Rate for Individual =

$$\left[\left(\left(\frac{\left(\frac{\left(\text{ULR} \times (\text{Ry})^{-\text{E}}\right) + \text{CntyCAT}}{\text{ResFac}} \right)}{\text{UnitFac}} \right) \times \text{TpFactor} \right) + \left(\frac{\text{PP}+\text{RP}+\text{QA}+\text{StCAT}}{\text{UnitFac}} \right) \right] \times \text{CLD}\,.$$

Given the formulation in equation 2, the rationale for each adjustment used to individualize rates (i.e. the yield ratio (Ry), the exponent (E), the type/practice factor (TpFactor), the coverage level differential (CLD) and the unit division factor (UnitFac)) are discussed below. The current methods for calculating these adjustment factors are described as well.

4.2. Yield Ratio

The yield ratio (Ry) is a mechanism to reflect the heterogeneity of risks at the insured unit level. The use of Ry implies that an individual's premium rate can be reasonably based on the magnitude of his/her own historical rate yield relative to the county reference yield. The individual rate yield is calculated based on a 4-10 year individual yield history reported by the producer when he/she signs up for crop insurance. The reference yield is based on the average of county yield estimates from the National Agricultural Statistics Service (NASS).

Because the ULR is based on county-level data, the implicit assumption when using Ry in equation 4.2 is that the county unloaded rate reflects the rate for an individual producer at or near the historical county average yield. The yield ratio allows for having different premium rates that depend on whether the individual yield experience is near or farther away from the mean county yield experience. As will be explained further below, using the yield ratio with a negative exponent means that individual farmers with rate yield higher than the NASS county mean yield will have lower rates (and vice-versa).

The implicit assumption about the "congruence" between reference yield and the county unloaded rate is important to the accuracy of the estimated premium rates. However, the reference yield is calculated based on county-level NASS data that include experience from both insured and uninsured farmers. On the other hand, the county unloaded rate is primarily based on county-level loss cost experience of only the insured pool of producers. This means that two separate bodies of data are used to calculate the reference yield and the reference rate. This practice is only valid when the following implicit assumption holds – the NASS county average yield (calculated from both insured and uninsured producers) is roughly equivalent to the long term average yield of the insured pool of producers from which the reference rate is derived. However, if there is an inconsistency in this assumption (i.e. the average yield of the insured pool is different from the producers in the NASS insured/non-insured pool), then the risk of loss is not accurately reflected in the premium rates.

Furthermore, it should be noted that reference yields used in the past have not been regularly updated, although in recent years the RMA has implemented a process to update reference yields.[7] It is also important to note that NASS data are not available for many crops, crop types, and cropping practices for which crop insurance contracts are offered. This necessitates use of proxy measures to obtain the reference yield parameter.

[7] According to the Rate Methodology Handbook, reference yields for a particular crop (in all counties) are only updated when there is a target rate review for the crop. In this updating procedure, the reference yield is updated if the current reference yield is outside a specified range of the transitional yield.

Using dated and proxy reference yields may also adversely impact the extent to which premium rates accurately reflect the risk of loss.

In light of these issues, RMA-commissioned a study, completed in 2006, which thoroughly examined the reference yield methodology and recommended a reference yield calculation methodology that uses rate yields from RMA experience data. The study emphasized the importance of regularly updating reference yields to avoid actuarial shortcomings. In addition, methods for updating reference yields in counties with thin data were developed.

4.3. Yield Ratio Curve and Exponent

The yield ratio curve, based on the negative exponent in equation 4.2, is part of a mechanism to individualize the county-level unloaded rate to reflect differences in expected loss costs for insured units depending on the relationship between the individual rate yield and the reference yield. As discussed above, this approach essentially implies that premium rates should be inversely related to individual average (rate) yields. That is, farmers with higher yields relative to the county have lower rates and those with yields lower than the county have higher rates.

As Milliman and Robertson (2000, p. 33) point out, the rationale for using this approach stems from RMA research that demonstrated that "on average, the probability of a loss is greater for producers with a yield lower than the average for an area and vice versa [for producers with yields higher than the area average]." This finding indicates that as an individual's mean yield increases relative to the county average; their proportional yield variability decreases such that it lowers the likelihood of an indemnified loss.[8] Hence, premium rates are structured to decline with increases in individual rate yields.

Currently, however, RMA has not established a method to update the exponents that determine the shape of the yield ratio curve. Based on an internal 2008 memo referring to a commissioned study about the exponents, the exponents currently in use appear to have been created to fit the yield spans used prior to implementation of the continuous rating system in 2001.[9] In that same memo, it was determined that sampling variability in the limited sample (4-10 years) used to determine the individual rate yield also plays a major role in the relationship between average yields and premium rates. This sampling variability makes it empirically possible to have a positive estimated exponent parameter. This finding was used to explain the extreme values of exponents estimated in an earlier

[8] These findings were also supported by work of Skees and Reed (1986) and Goodwin (1994). Although it should be noted that Goodwin (1994) found the relationship between mean yield and relative yield variability to be "tenuous", with considerable variation among farms. Based on this, Goodwin (1994) recommended incorporation of observed farm-level variation or other observable risk characteristics of the farm into the rating process.

[9] Prior to the continuous rating system, discrete "yield span" classifications were defined for specified ranges of Ry and premium rates discretely declined for higher yield span classifications.

2007 RMA-contracted study. This study estimated the exponents using OLS regression of a loss cost equation with a “linear in parameters” specification (i.e. log-transformed).

Given the perceived shortcomings of the 2007 study the aforementioned 2008 memo developed and recommended an alternative estimation approach using nonlinear least squares (NLS) regression. This approach was found to have a narrower range of estimated exponents than the estimates from the earlier 2007 study. And the resulting exponents from the NLS regression approach were significantly lower (resulting in a flatter yield ratio curve) than the current exponents and the exponents from the 2007 study. It was noted in the memo that the smaller exponent estimates may be due to the preponderance of zero loss cost ratios in the data.

4.4. Type-Practice Factors

The target rate in equation 4.1 uses insurance experience data aggregated for all crop types and cultural farming practices at the county level. However, different crop type/practice combinations often have different risk characteristics. These differences need to be addressed in order to develop appropriate rates for each crop type/practice combination.

The current RMA rating procedure for type/practice is described in an internal document titled “RMA Type/Practice Rating Methodology Interim Underwriting Guidelines”. In the current system, crop type/practice is accounted for by multiplying the variable rate component of the county target rate by a type/practice factor (TpFactor) for each type/practice combination. In constructing these type/practice factors the RMA uses experience at a multi-county level, at the state level, or at a multi-state level. Deciding on the proper level of aggregation for any crop and region is a matter of balancing two primary considerations: homogeneity of risks and volume of data. The risks associated with each crop type/practice are more homogeneous at a disaggregate level; however, aggregation provides a greater volume of data. The approach taken to address this problem varies by region. For example, in deriving the TpFactors for irrigated and non-irrigated practices in the Western States, grouping a smaller number of geographically clustered counties within the state is more typical since the average rainfall (and the importance of irrigation) changes significantly over shorter distances. In contrast, the Eastern States have rainfall patterns that are more stable across greater distances and grouping more counties, whole states or multiple states may be appropriate. Determination of the county groupings for use in developing type/practice factors is largely left to the subjective judgment of the RMA regional offices. A credibility procedure similar to that used to determine the unloaded county target rate could be used to weight the experience of smaller aggregations against larger group data. Such a procedure would automatically give more weight to an indicated differential that is different from the neighboring experience provided that it is consistent across time and supported by a sufficient volume of experience data. We also note that, in many cases where one practice is rare, there may be no difference in the rates, perhaps because the local experience is of insufficient volume to be credible. In that case, it would be appropriate to use more aggregate data to determine an appropriate differential.

Once the level of aggregation for a particular region has been determined, the TpFactors are calculated by dividing the type/practice-specific loss cost ratios (LCR) for the region by the aggregated regional LCRs derived over all crop type/practices. Units with "mixed" types or practices are not used in the TpFactor calculation. The reason for this is that when an insured unit contains multiple crop type/practices it is not possible to segregate losses by type/practice. While this procedure involves discarding data it also avoids the introduction of data on which the type/practice effect cannot be accurately measured.

The regional factor calculated in the previous step is referred to as the "raw" factor. The final step in calculating the TpFactors for a county is adjusting the raw regional factor for the historical liability proportion for each type/practice combination in the county. Here we provide a description of this process for developing TpFactors to support our recommendations in chapter 6. To be clear about when regional versus county data are used, we subscript variables with *R* when they are measured at the regional level and *C* when measured at the county level. Further, in this example we consider a region and county with two type/practice combinations, subscripted by 1 and 2.

Step 1: Calculate regional *simple average loss cost ratio* over a period of *N* years for each type/practice and for all type/practices combined (here we use the subscript *T* for total).

(Eq. 4.3) $$SALC_{R1} = \frac{1}{N}\sum_{i=1}^{N}\frac{Indemnity_{R1i}}{Liability_{R1i}}, SALC_{R2} = \frac{1}{N}\sum_{i=1}^{N}\frac{Indemnity_{R2i}}{Liability_{R2i}},$$

$$SALC_{RT} = \frac{1}{N}\sum_{i=1}^{N}\frac{Indemnity_{RTi}}{Liability_{RTi}}.$$

Step 2: Calculate raw regional type/practice factors.

(Eq. 4.4) $$RF_{R1} = \frac{SALC_{R1}}{SALC_{RT}}, RF_{R2} = \frac{SALC_{R2}}{SALC_{RT}}.$$

Step 3: Calculate $Extension_C$, which is the county liability-weighted average of RF_{R1}

and RF_{R2} . Here $LW_{Cj} = \sum_i^N Liability_{Cj}/\sum_i^N Liability_{CT}$ for county C and type/practices $j = 1,2$.

(Eq. 4.5) $$Extension_C = LW_{C1} \times RF_{R1} + LW_{C2} \times RF_{R2}$$

$$= LW_{C1} \times \frac{SALC_{R1}}{SALC_{RT}} + LW_{C2} \times \frac{SALC_{R2}}{SALC_{RT}}.$$

Step 4: Calculate the final county TpFactors for type/practices $j = 1,2$.

(Eq. 4.6) $$TpFactor_{Cj} = \frac{RF_{Rj}}{Extension_C} = \frac{SALC_{Rj}/SALC_{RT}}{LW_{C1} \times (SALC_{R1}/SALC_{RT}) + LW_{C2} \times (SALC_{R2}/SALC_{RT})}$$

$$= \frac{SALC_{Rj}}{LW_{C1} * SALC_{R1} + LW_{C2} * SALC_{R2}} .$$

It is instructive to consider the total amount of premium that would be charged in a county using these TpFactors. Here we assume that the TpFactors are applied to the simple average loss cost ratio for the county ($SALC_{CT}$), which is calculated by averaging the individual loss cost ratios, across all practices, for the county for the N year time period.

(Eq. 4.7) $$Premium_{Cj} = TpFactor_{Cj} \times SALC_{CT} \times Liability_{Cj}$$

$$= \frac{SALC_{Rj}}{LW_{C1} * SALC_{R1} + LW_{C2} * SALC_{R2}} * SALC_{CT} \times Liability_{Cj} .$$

(Eq. 4.8) $$Premium_{CT} = Premium_{C1} + Premium_{C2}$$

$$= \frac{SALC_{R1}}{LW_{C1} * SALC_{R1} + LW_{C2} * SALC_{R2}} * SALC_{CT} \times Liability_{C1}$$

$$+ \frac{SALC_{R2}}{LW_{C1} * SALC_{R1} + LW_{C2} * SALC_{R2}} * SALC_{CT} \times Liability_{C2}$$

$$= SALC_{CT} \left[\frac{SALC_{R1} * Liability_{C1}}{LW_{C1} * SALC_{R1} + LW_{C2} * SALC_{R2}} + \frac{SALC_{R2} * Liability_{C2}}{LW_{C1} * SALC_{R1} + LW_{C2} * SALC_{R2}} \right]$$

$$= SALC_{CT} \times \left[\frac{SALC_{R1} * Liability_{C1} + SALC_{R2} * Liability_{C2}}{Liability_{C1} * SALC_{R1} + Liability_{C2} * SALC_{R2}} \times Liability_{CT} \right]$$

$$= SALC_{CT} \times Liability_{CT} \ .$$

Equations 4.7 and 4.8 show that the process followed by the RMA in deriving the TpFactors for a county involves use of regional loss cost ratio relationships and county liability weights to derive county type/practice factors which collect the same amount of premium as would be collected if the simple average loss cost ratio for the county (combining all types/practices) were multiplied by total county insured liability. In our opinion the RMA's process for using the derived TpFactors to distribute the premium among types and practices is reasonable. However, as discussed above and shown in equation 4.2 these TpFactors are only applied to a portion of the county premium rate (i.e., only to a proportion of the historical county loss cost ratio). The derivation above demonstrates that in order to maintain the indicated type/factor differentials the TpFactors would need to be applied to other portions of the premium rate. This issue is discussed further in Chapter 6.

4.5. Coverage Level Differentials

The county-level rate in equation 4.1 is derived at the 65% coverage level. The individual rates at different coverage levels in equation 2 are then calculated by scaling the 65% rate using coverage level differentials (or coverage level rate relativities). Prior to 2004, fixed coverage level differentials were used to adjust the county level rate that is assumed to be accurate at the 65% coverage level. This means that the coverage rate differentials were the same regardless whether the county level rate in equation 4.1 was 0.01 or 0.50; or whether the crop was corn or soybeans.

However, the findings and recommendations of a RMA-commissioned study in 2002 led to the adoption of variable coverage level differentials which depend on the crop and county-level base rate.[10] Specifically, this study found that the coverage level differentials should decrease as the base rate increases. The logic is as follows. Consider two regions: one a high risk region where the probability of an indemnity at the 65% coverage level is high and one a low risk region where the probability of an indemnity is low at the 65% coverage level. Because there is more probability of a yield below the guarantee for the high risk region there must be less probability of getting a yield above the guarantee. As a result, when we move from the 65% coverage level to the 85% coverage level, the rate will tend to increase more for the low risk region because the probability of a yield between 65% and the 85% coverage level will tend to be higher than that of the high risk region. Therefore, the ratio of the 85% premium rate to the 65% premium rate for the low risk region will tend to be higher than that for the high risk region.

The variable coverage level differentials are derived using a robust median regression method to estimate a model specification where the implied coverage level differential (from unit level historical loss cost data) is a function of the following: coverage level (and its squared term), the county-level base rate at the 65% coverage level (and its squared term), and an interaction between the coverage level and the county-level rate at the 65% coverage level:

(Eq. 4.9) $$\text{Coverage Level Differential} = \beta_0 + \beta_1 \times \text{coverage level} + \beta_1 \times \text{coverage level}^2$$
$$\beta_4 \times \text{rate}_{65} + \beta_5 \times \text{rate}_{65}^2 + \beta_6 \times \text{coverage level} \times \text{rate}_{65}.$$

Estimated parameters from this model, with actual coverage level differentials calculated from the historical unit level yield experience, underpin the development of coverage level differentials that vary with base rates and that are tailored to the loss experience for different crops.

[10] The recommendation of moving to a variable coverage level differential was also supported by the article of Babcock, Hart, and Hayes (2004).

Another insight emerging from the RMA-commissioned study in 2002 is the need to account for endogenous risk changes associated with insuring at higher coverage levels (i.e. lower deductibles). It is a widely accepted that economic incentives to produce are reduced at higher coverage levels. The challenge is to determine the magnitude of this effect at different coverage levels and incorporate this in the coverage level differential above (i.e. the endogenous risk is not factored in the estimation of equation 4.9). The endogenous risk behavior is incorporated in the coverage level differential by calculating an endogenous risk factor using historical loss cost data at a specific coverage level and comparing it to an "implied" loss cost used in estimating equation 4.9.

Note that the variable coverage level differentials, including the endogenous risk factor, have been incorporated in the rates for corn, soybeans, and wheat and some other crops. By 2009, it is expected that most continuously rated crops will move to the variable coverage level differential approach.

4.6. Unit Division Factor

The federal crop insurance program provides coverage for different "unit" formats or structures. Each parcel of land that is insured independently of other parcels is called a "unit". Currently, there are four unit structure options available: optional, basic, enterprise, and whole-farm. The first three unit structures are available for APH yield insurance, CRC, and RA, while the whole-farm unit is only available for RA. Basic units consist of all acreage of the crop in a county held by the insured under identical ownership. Optional units are subdivided basic units, with the subdivision based on location (typically by separate sections) and production practices. Enterprise units reflect a higher level of aggregation, combining all of a producer's financial interest in a crop in a county. A whole-farm unit is at an even higher level of aggregation, combining all of the insured acreage for two or three crops in a county.

A unit division factor (UnitFac) is used to reflect the differences in risk (or loss experience) among the different unit formats. Loss cost experience in a county is implicitly assumed to reflect basic unit experience. These loss cost ratios are factored up by a UnitFac of 0.9 in equations 4.1 above to convert the county target rates to the optional unit level. A 10% discount is then given for units insured at the basic unit level. Where enterprise units are available under APH and CRC, the discount depends on the total acres in the aggregated enterprise unit. For RA, enterprise unit discounts are based on the number of separate sections or section equivalents contained in the unit. The multiplicative unit division factors contained in the actuarial documents can be viewed as discount factors for insuring at a higher level of aggregation than the optional unit level.

The actuarial logic for the unit division factor (or unit discount) is based on the risk reducing effect of insuring at a higher level of aggregation. The reduction in overall risk associated with units that are combined rather than having those units separately insured arises from an aggregation effect that is similar to the risk reduction implied by standard portfolio theory. Aggregation of individual risks (insurance units in this case) that are not perfectly correlated reduces overall (portfolio) risk. This notion is related to the theory underlying farm portfolio selection, where the number of farm enterprises affects overall farm level risk by reducing non-systemic or diversifiable risk (see Turvey, Driver, and Baker 1988, for example). In farm portfolio selection, the producer allocates portions of acreage to different enterprises with less than perfectly positively correlated yields, which results in lower overall risk. As more subunits are aggregated to form the "unit portfolio" to be insured, the level of risk and the premium associated with the aggregated unit should decline.

However, the use of a constant proportional discount of 0.9 when insuring basic units implicitly assumes that the difference in risk (or loss experience) between these two unit formats is fixed across different unit characteristics (e.g. unit size), across crops, and across regions. Previous studies have shown that, in general, loss experience for optional units is higher than for basic units, and that the overall difference was not significantly different from the current 10% fixed differential (See Knight and Coble, 1999; Schurle, 1996). If a fixed discount is to be used, then on average the current 10% basic unit discount is reasonably consistent with loss experience.

Notwithstanding the finding above, a 2004 RMA commissioned unit structure study recommended that a variable (rather than fixed) unit discount approach would be a more appropriate procedure when rating different unit formats. The study results indicated that the magnitude of appropriate discounts differs among crops and is strongly affected by the coverage level chosen by the producer. The appropriate discount also depends upon other characteristics of the insurance policy including the total number of acres in the aggregated unit and the average premium rate for the aggregated unit. These factors are easily derived from information that is currently collected on every insurance policy. In light of these findings, the Board of Directors of the FCIC has approved adoption of the variable unit discount approach but the discounts have not yet been implemented.

5.0 Assessment of Alternative Procedures to Develop APH Yield Rates

5.1 Objectives of RMA Rating

As we begin our critique of the RMA actuarial system, it is helpful to revisit the objective of the rating system. Legally, RMA has a clear actuarial objective defined in terms of a loss ratio. The Federal Crop Insurance Act (as amended February 17, 2009) defines the loss ratio as follows:

> *LOSS RATIO.—The term ''loss ratio'' means the ratio of all sums paid by the Corporation as indemnities under any eligible crop insurance policy to that portion of the premium designated for anticipated losses and a reasonable reserve, other than that portion of the premium designated for operating and administrative expenses.*

This legal definition speaks of anticipated losses rather than past or current losses. It also defines the premium as the premium designated for loss expenses and a reasonable reserve. However, operating expenses and administrative expenses are not included in the loss ratio calculation. Also, while not explicitly stated, crop insurance subsidies are separately computed and the premium used in this loss ratio calculation is the total premium associated with the policies sold. Thus, this definition implies RMA must assess actuarial soundness by comparing expected future losses to premium dollars that will be collected.

The Federal Crop Insurance Act goes on to specify an explicit target for the projected loss ratio.

> *PROJECTED LOSS RATIO.—The Corporation shall take such actions, including the establishment of adequate premiums, as are necessary to improve the actuarial soundness of Federal multiperil crop insurance made available under this subtitle to achieve an overall projected loss ratio of not greater than 1.0.*

As mentioned earlier, for many years RMA was mandated to achieve an overall loss ratio of 1.075. However, the Food, Conservation, and Energy Act of 2008 revised the target loss ratio to 1.0, which created a budget savings but also put increased pressure on RMA to ensure actuarial soundness. The implication of these targets for RMA actuaries is to mandate that the program should collect premiums sufficient to cover indemnities. However, RMA is also directed in the Federal Crop Insurance Act to, "…promote the national welfare by improving the economic stability of agriculture through a sound system of crop insurance …" Thus, RMA must balance making a program broadly available to producers, which improves national welfare, while still maintaining actuarial soundness.

Note also that the legislative mandates do not specify the level at which the targets must be achieved. It is a valid question whether the mandates must be maintained at the national level, crop level, or at a less aggregate level. RMA is to make a compelling case that rates charged will be sufficient to cover future losses. Ideally, this challenge would be achieved by meeting actuarial targets at every level of the program down to the policy level. However, when the legislation speaks of “anticipated losses” or “projected loss ratios” a context of mathematical expectations is implied. Therefore, it is an increasingly demanding goal to achieve actuarial targets at more disaggregate levels and it is more difficult to assess whether targets are met. This is true of all insurance designs and not unique to crop insurance. To put this in context, RMA insured over 2.4 million APH, RA, and CRC insured units in 2009 (September 2009 RMA Summary of Business Reports). Since the rate for each of these units is in effect a mathematical expectation of the loss cost ratio for that unit, then one has the opportunity to evaluate the accuracy of rates on each insured unit. However, only one random outcome for each unit is observed in 2009. This is valuable information, but completely inadequate to draw a statistically valid conclusion. Statistical confidence in assessing rates can only be achieved with a sufficiently large sample.

Another way of looking at the target achievement level is to note that if it were possible to accurately predict the experience for every producer every year then every producer could be charged premiums exactly equal to the producer’s losses – completely eliminating the insurance. Insurance must always be provided on a pooled basis, where total premiums match collected losses, recognizing that most insureds in most years will not experience a loss greater than the premiums paid. Rate adequacy can and should be determined for the system as a whole. Adequacy at this level ensures that the system is financially sound. In addition, in order to avoid having one group subsidize coverage for another, it is necessary to identify groups of sufficiently similar risks so that the long-term average (“expected”) losses for everyone in each group are about the same.

5.2 Context of RMA Rating

Given the objective mandated for the Federal crop insurance program, our review team has evaluated the specific nature of the rating challenges confronting RMA. We find seven features of the portfolio of crop yields that RMA insures to be critical determinants of how RMA should approach rating

Nature of the Risks Insured

Crop yields are subject to a variety of risks: frost, floods, drought, extreme temperatures, hail, disease, insects, and other perils. The products reviewed in this report are multi-peril coverage designs such that a reduction in yield (or revenue) is measured without specifically determining how much each peril contributed to the loss. This is in part due to the fact that crop yields are the result of the interactions among several factors. For example, this makes it quite difficult to sort out how much of a yield loss is due to high temperatures versus inadequate rainfall.

Because so many of the risks driving yield losses are related to environmental conditions, assessing crop insurance yield risk probabilities is predicated on an accurate assessment of the probability of these events. In effect, at least with respect to the systemic component of crop yield risk, it may be argued that we only obtain one empirical observation for each crop in a county each year. This creates an inherent tension in rating. Actuaries would clearly like to have a long time series of experience for rating purposes in order to accurately determine the probability of historic loss events. For example, a long time series of data would be required to reliably estimate the frequency of occurrence of a flood such as the one observed in the Midwest in 1993. Conversely, because crop production systems have changed and the crop insurance program itself has changed, older loss experience is likely to be less reflective of the current program than more recent experience.

Correlation of Losses

Many loss events are geographically correlated across broad regions. A drought often spreads across several states. A flood may affect low-lying farms in several states. Conversely, hail losses tend to be localized – a characteristic amenable to insurance which is a reason private hail-insurance coverage has been successfully offered for decades. The multiple-peril yield insurance policy shares at least some of the characteristics of coastal property insurance where weather is a driving factor and a high percentage of liability may be indemnified in the same period. This characteristic makes rating more difficult than if losses were truly independent. Much more would be learned from a short time-series of experience with uncorrelated risks. For example, automobile collision rates might be credible if based on only a few years of data because losses are effectively independent.

Broad Availability

In administering a government-funded insurance program, RMA is tasked to make insurance broadly available. This may take on various forms and has a number of implications. By making insurance broadly available, RMA is at times asked to insure crops in regions where production is quite thin. For example, 25 percent of counties where RMA sold corn insurance (APH, CRC, and RA) had less than 1100 acres insured in 2008. Further, while the preponderance of the RMA program business (83% of insured acres) is in the “big four” crops (corn, soybeans, wheat, and cotton) RMA also offers yield insurance on 105 other crop programs. In many cases these crops are widely dispersed with heterogeneous growing conditions such that aggregation of experience across regions is questionable. Thin data regions and crops pose particular actuarial challenges. Private companies would likely avoid the most difficult of these cases because the potential volume of business would not support the cost of program administration and due to the difficulties in developing valid rates. As a government agency, RMA does not attempt to maximize profit. In fact, the agency operates under a political imperative to extend coverage to regions where the potential volume of business is low and accurate rate development is challenging.

Heterogeneity of Risks

For a variety of reasons producers within a very small region or county may or may not have similar risk levels. While weather events in a county may be highly correlated, other factors may influence losses as well. Soil quality, slope, and elevation can strongly affect production risk. Management choices and production systems unique to the farm may also influence yield risk. For example, investment in costly irrigation systems may greatly reduce yield risk. Similarly, producers with superior management skills may be significantly less risky than a neighbor. Thus, while there is often a benefit to combining experience from nearby producers, there is often a significant influence of individual-specific risk characteristics on actuarially fair rates.

Available Producer Experience

Another aspect of making crop insurance broadly available is the amount of data available for an individual insured unit. From an actuarial perspective it would be desirable to have a long time series of yields from an insured unit to assess risk. However, due to crop rotations, changes in cropping patterns, and other factors, RMA frequently insures units with 4 or fewer historical yields. This challenges the rating system even when a significant amount of information from surrounding farms is available.

Perils Covered

We also note that the terms of coverage Congress has mandated for RMA include several protections that go beyond what would normally be considered as a part of the yield risk on a crop. For example, RMA coverage includes protection against prevented planting, replanting cost, and quality losses – none of which is usually reflected in yields that are measured and reported on a per planted acre basis.

Voluntary Coverage

The purchase of crop insurance is a decision made by each producer. There is no mandate, and producers must weigh the cost of coverage against their perception of the potential for loss. Rates that do not accurately reflect relative risk result in adverse selection. That is, potential insureds who are offered rates that are too high opt out of the program while potential insureds whose rates are too low purchase coverage at prices that do not cover their losses. The result is an entire system where total premiums collected are lower than the covered losses. It is essential, then, that rates reflect expected experience.

5.3 Assessment of Alternative Rating Approaches

Given the context in which RMA must set rates, we now turn to assessing alternative rating systems. While the legislative mandate to RMA states that actuarial soundness is to be measured in terms of anticipated losses and projected loss ratios, these outcomes must be evaluated with data available in the current period. This is a common forecasting challenge and is encountered in private insurance as well as in the crop insurance program. Historical experience is frequently used, but often it must be adjusted to account for program changes or structural changes over time. Various statistical techniques can be used and will be discussed in our further review of RMA rates.

5.3.1 The Use of Unadjusted Loss Ratios

Because the RMA actuarial standard is defined in terms of a *projected* loss ratio, program actuarial soundness is often assessed by computing a *historical* loss ratio. While sometime suggestive of performance, a simple loss ratio is a crude way to assess program performance with historical data. By unadjusted loss ratios we refer to computed values based on aggregated data (such as those available from the summary of business reports available from RMA). Typically the indemnities and premiums for some crop/geographic area are summed across some period of years and the loss ratio computed. Mathematically this may be written as

(Eq. 5.1) $$Loss\ Ratio_R = \frac{\sum_1^T \sum_1^C Indemnity_{tc}}{\sum_1^T \sum_1^C Premium_{tc}}$$

Where the subscripts *R* reflects region (e.g. state or nation); *C* indicates county; and the subscript *T* indicates time period. For a variety of reasons the use of unadjusted historical loss ratios can lead to erroneous conclusions. Some of the most obvious reasons are as follows.

The unadjusted loss ratio approach implicitly applies the premium rates of the past to the future. In many cases we know that rates have evolved through time and may now be substantially lower or higher than they were at the time of a historical loss. It is clear that loss ratio experience does not predict future losses if rate changes over time are not recognized.

Because of the nature of the risks involved, short time periods are likely to be misleading. Yield and price risk both tend to be characterized by infrequent but large shocks which drive the actuarially fair rate. If crop insurance insured a risk like automobile collision a short historical experience base might be sufficient. However, crop insurance losses in many cases are much more similar to coastal property insurance which requires sophisticated modeling of weather probabilities. This is especially true for low risk regions/crops or low coverage levels. Thus, a loss ratio computed over a few years can lead to grossly erroneous conclusions regarding actuarial soundness and should not be relied upon.

Crop insurance program participation has grown dramatically over time. This results in relatively more weight to recent years when loss ratios are computed as in equation 5.1, which implicitly weights each year's loss ratio by premiums paid in the year. It could be argued that recent experience is more relevant and that recent experience may be more credible because more farms are participating. For example, the Iowa corn program earned $90.4 million of premium in 1997 but almost $575 million in 2008. This means the 2008 experience is associated with 6.35 times more premium. However, we doubt that anyone would argue that the weather in 2008 should be given 6.35 times more weight than the weather in 1997.

A number of policy attributes can profoundly alter the risk distribution of crop insurance experience. This can imply the unadjusted loss experience is no longer representative of the current or future loss expectations. Some county/crop programs have experienced a significant shift in the mix of types or practices. An example would be a county where irrigation has increased or decreased. Similarly, coverage levels have tended to increase in recent years. Also, the crop insurance program has experienced significant expansion of insurance plans since the advent of revenue insurance in 1996.

The issues raised here clearly show that simple historical loss ratios cannot be used to support strong conclusions about future loss expectations. Fundamentally, short loss ratio series can grossly misrepresent expected loss ratios as they suffer from the error resulting from a limited sample of weather and price shocks. Conversely a longer loss ratio series will increasingly be subject to criticism for failing to account for program changes over time. Ultimately, valid actuarial assessment of loss experience will combine a sufficiently large sample to accurately reflect random events with reasonable adjustments to account for program modifications.

To illustrate the effect of using a short time series of loss experience to evaluate the crop insurance program, we conducted a stochastic simulation which allowed us to define a typical crop insurance program where the true underlying probabilities, and thus the actuarially fair premium rate, are known. We then evaluate the observed loss ratios realized with premium rates that are known to be actuarially fair. We conduct this simulation using the Anderson, Harri, and Coble (2009) multivariate random simulation technique. This technique allows for multiple random variables to be produced with known correlation between the random variables and mixed marginal distributions.

This simulation is quite simple in that we generate a yield distribution from a beta parametric distribution with shape parameter alpha equal to 3 and shape parameter beta equal to 2. The upper bound and range of the beta distribution is from zero to 120 bushels per acre. In this simulation analysis we also specify the error term or the random variability of this crop to be centered on a mean of zero, but have a negatively skewed tail as one would expect in a highly productive cropping region which suffers infrequent but severe losses. The simulation also assumes that there is a trend in yield of 1.5 bushels per acre per year and that the starting expected yield at the beginning of the time series is 75 bushels per acres. The simulation is carried out for a number of years and assumes that the yield variability for this crop is directly proportional to the mean yield. What results is a random deviation that increases over time as the mean increases as well. This will result in an exact loss cost and exact rate for the program. To further specify the stochastic simulations, the coverage level is set to 0.65 and we then calculate the actuarially fair premium rate for this stochastic specification by doing 100,000 random draws of these data.

We then evaluate what is observed when various moving averages of the loss ratio are used to rate the program. We use a 40-year, 24-year, and 8-year moving average to set rates and then evaluate what happens to the observed loss ratio when the moving average rate is applied rather than the known true rate. In Figure 1 the results from an eight-year, a 24-year, and a 40-year moving average rate are reported. This is just one time path through the data and we use the first 40 years of the series to begin the 40-year moving average and then we model an additional 60 years of the crop insurance program. The true loss ratio in this figure is 1.0 by construction. The observed loss ratios vary dramatically from the 1.0 level. The most extreme deviation is that for the eight-year moving average loss ratio. The 24-year moving average is more stable and the 40-year moving average is more stable still. However, even with a 40-year moving average of a loss ratio, there are instances where the observed loss ratio is more than 50 percent different than the true loss ratio for this series of data. We use this illustration to point out that with negatively skewed and relatively low probability events, one is likely to observe significant periods where the loss ratio is quite different than the true loss ratio. We also conducted 1,000 simulations of these alternative loss ratios and find that the standard deviation of the loss ratio increases as the number of years used to calculate the loss ratio decreases. The standard deviation for a 40-year moving average loss ratio is 0.25 whereas the standard deviation for an eight-year loss ratio is 0.29. This is indicative of the greater uncertainty of the loss ratios based on data for short time periods.

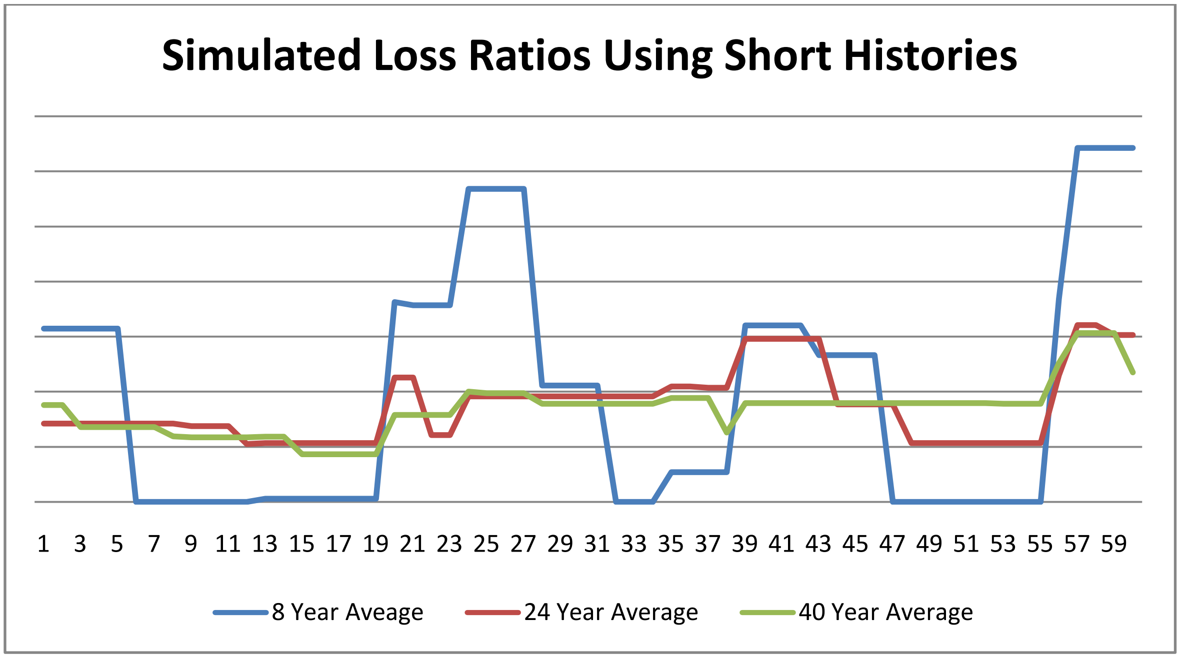


Figure 5.1

As mentioned earlier, RMA is mandated to set rates such that the projected loss ratio is 1.0. For reasons we have already discussed, this is difficult to assess and simplistic approaches to assessing program loss ratios can be misleading. Frequently, when aggregate loss ratios are observed, especially over relatively short periods, the loss ratio for some crop/region programs will be much higher than for another region. It is often perceived that losses in one region are used to compensate for losses in another region. Our review of the RMA rating system leads us to conclude the following regarding these concerns with regard to actuarial soundness.

The rating system described in Section 4 shows the loss experience of a policy for a particular crop in a particular state will not affect the base rate for a policy in any other state[11], nor will it affect the rate for another crop in the same state. Clearly, loss experience for a crop in a given county has a strong effect on the rates within that county. Through the credibility system, losses for a crop may influence the rate for the same crop in an adjoining county. In cases where the data by type/practice is insufficient to determine the appropriate differentials, RMA aggregates data across a wider area, but only for the purpose of determining the appropriate discount or surcharge. Finally, through the catastrophic loading procedure there is potential for losses in one part of a state to significantly influence the rate in another part of the state for the same crop. Beyond these relationships, we find no evidence that losses for one policy can affect the

[11] Actually, the experience for a policy in a border county in one state may have some effect on the rates in a neighboring county in another state through the credibility system, but the reach out of state is never beyond a contiguous county

rates for another policy for the major crops[12]. Further, since RMA draws upon CCC funds for program costs rather than from firm equity as a private firm would, any excess losses are absorbed by the U.S. Treasury.

5.3.2 The Use of a Yield Simulation Based Rating

Dealing with Risk Heterogeneity

The RMA rating system cannot simply reflect expected losses for a representative farm within a county. Rather the RMA rating system is designed to develop a schedule of rates that accurately represent the risk of various farms within the county. For example, a county may have different crop types and practices, a county may also have farms with greatly differing yield potential because of soil, topography, or producer management skills. RMA must develop a rating system that is valid across all these farms and, importantly, that has the flexibility to reflect the heterogeneous risk characteristics.

If yield a distribution or yield simulation approach were used, there would need to be a great variety of yield distributions even within a single county. Most of the yield distribution approaches we have observed fit a univariate farm-level distribution or use combined information from distributions of farm and county yields. However, this approach does little to address within county risk heterogeneity and does not utilize data from adjoining or similar farms to augment the information used to rate a particular unit. Multivariate or conditional distribution fitting is possible but complex, and this approach typically relies upon strong assumptions regarding the appropriate parametric distribution and other specification issues. In contrast, loss experience rating typically categorizes insured units into pools of similar risk and uses experience from the pool to derive a premium rate. This is a well-accepted insurance rating approach and widely used in property and casualty insurance.

Convergence of Rates with Losses

A valid insurance rating system needs a mechanism by which rates and the observed experience are brought together and expected to converge. In property and casualty insurance, loss experience often serves as the primary basis for rating. Sometimes this experience is augmented with simulations, but typically the only time that you would see a simulation based approach for property and casualty insurance in the private sector is when the available historical experience provides an inadequate basis for determining the appropriate rate. Simulation based approaches are used almost universally in rating property catastrophe exposures such as earthquakes and hurricanes because the observed experience does not reflect either the full range of potential outcomes or the current

[12] Minor crops are sometimes rated based on aggregate experience over a larger area due to lack of credibility at a finer level of geographic division, but the ratemaking for even minor crops has no effect on the rates for other crops.

distribution of exposures. At considerable expense, a handful of comprehensive catastrophe models have been developed that can overlay several hundred thousand potential weather scenarios or earthquake events on an insurance company's current set of insureds and determine the insurance losses under each scenario. The insurance losses are influenced by the severity of the weather or earthquake event and also by the individual construction characteristics and exact geographic location of each insured building. Expected losses for a given combination of storm, location and construction are determined by a team of experts including meteorologists, engineers and actuaries. The expected losses are the average insured losses over all of the hundreds of thousands of scenarios. Typically, insurers in the United States purchase the results of property catastrophe models (or the models themselves) from modeling companies rather than developing in-house models due to cost constraints and lack of expertise. While it is theoretically possible to construct a similar model for crop insurance, the number of required variables is staggering, and we believe that the cost of constructing such a system would be prohibitive. Technological change would necessitate frequent updating or extensive revision of such models at a cost that would be even more prohibitive.

On a related note, within a county RMA is required to provide rates for individuals with a variety of risk characteristics. In many cases this implies that there are production practices or yield expectations of farms within a county where the supporting data for that particular farm or type of farm is relatively thin. It is essential for the RMA rating system to be structured so that information from similar farms in a county can be used to infer the appropriate rate for a particular farm unit. But that would also take into account the differences in expected yield and expected variability of those farms. This is a particular challenge that RMA confronts in its rating system. It is our opinion that the lose experience based system used by the RMA is more robust than simulation approaches in meeting this challenge.

Losses Not Captured in Yield Data

A reason that loss experience base rating has a strong advantage relative to a yield simulation based approach is that the crop insurance program indemnifies losses that are not normally reflected in planted acre yields. In particular, prevented planting provisions may indemnify a producer and then allow the land to be fallowed or released to another crop. In either case, a farm yield series would not normally reflect this indemnity. Rather it would likely show zero acres planted. Similarly, the replant payment provision, indemnifies producers for the cost of replanting when an adequate stand is not established on the first planting. Often a crop is grown and harvested after replanting occurs. Farm yield data would typically consider the replanted acres as the crop acres. Suppose a unit receives a replanting payment, is then replanted, and a normal yield is achieved on the replanted acreage. Yield per planted acre data would reflect zero loss, but a crop insurance indemnity would have been paid. A third problem is quantifying quality loss. Quality loss occurs when the production to count on the insured unit has low value due to below average quality attributes.

These three sources of losses are important examples of where crop insurance indemnities are incurred but yield loss may not be recorded, or the magnitude of the indemnity is not accurately reflected in a realized yield loss. Therefore, we have reason to believe that there is a component of the indemnity that is not well represented by the standard yield distribution. Loss experience provides a measure of these indemnities that is consistent with what is actually triggering and causes losses as opposed to a yield simulation based approach which is likely to omit these relevant causes of loss.

Challenges for Using Yield Simulation Based Rating

The estimation of parametric, semi-parametric or even non-parametric yield distributions has been shown to be empirically feasible. However, a long series of data is required to obtain credible estimates of even the mean yield, much less the distribution. In addition, as noted in the paper by Harri et al (2009b), there is a great deal of disagreement among researchers regarding the appropriate specification of yield distributions. This lack of consensus is largely driven by the fact that observed yield distributions tend to be inconsistent across region, production potential, soil types, etc. This makes the modeling of yield variability extremely difficult in the context of insurance rating because either a large number of distributions must be estimated or assumptions must be made about the underlying distributions that may not be reflected well in the data for many subsets of experience. Since insured losses occur toward the tail of the distribution rather than near its median, parameter and model error in the estimation of the yield distribution are compounded when the yield distribution is translated into insured losses.

We also note that the heterogeneity of yield distributions and the disagreement among researchers regarding appropriate yield distribution estimation is in stark contrast of what one observes in the literature on price distributions. That literature is quite consistent, that the log-normal distribution is generally accepted, and importantly prices are quite homogenous across regions. In other words, a corn price distribution in western Kansas is not expected to be radically different than the corn price distribution in Ohio or North Carolina. Price variability measured in one location is quite helpful in estimating price variability in another region. With yield distributions there is relatively little that we learn as we move from one crop to another or from one location to another. This suggests that yield simulation based rating would have to estimate a multitude of yield distributions using approaches that are frequently disputed, perhaps also indicating that a model that fits the available data well might not be a very good predictor of future experience.

In-Sample Fit

Another aspect of rating with a yield simulation approach is the problem of in-sample fit or, in other words parameter uncertainty. The standard approach when using a yield distribution for an actuarial study is to estimate the appropriate yield distribution using a chosen estimator to find the shape of the distribution. The parameters are estimated with a degree of uncertainty and in relatively short yield series the degree of uncertainty is often quite large. Typically after the parameters of the yield distribution are estimated the distribution is integrated, either analytically or numerically, to the coverage level to obtain expected crop insurance indemnities. This is a fairly straight forward process. However, the results obtained depend on the parameter values. It has been shown by Norwood, Roberts and Lusk (2004), and others, that this should be done using an out-of-sample approach.

In terms of model fitting and forecasting ability, it is our opinion that from an actuarial standpoint it is necessary to recognize that rating of crop insurance is inherently an out-of-sample process. By that we mean that each APH yield and rate offered to a producer is in effect a forecast of the expected yield and indemnity for that particular insured unit. When actual indemnities from the program are measured, one inherently captures the forecasting error of the rating system. In other words, if the APH does not accurately reflect the expected yield in every case, and that has an influence on rates, that uncertainty is built into the observed losses. Therefore, we recommend that any approach used to rate crop yield insurance should be based on out-of-sample evaluation. Conversely, within-sample fitting of parametric distributions will tend to underestimate the losses that would be observed in a crop yield insurance program.

Available Data

Another challenge for the yield simulation based approach to crop insurance rating is that it is extremely difficult to obtain a long enough yield series at the appropriate level to estimate distributions with a sufficient degree of confidence. In other words, the more observations that are available to use in estimating a parametric distribution, the greater the confidence in the estimates obtained. To be credible one would need a long time series of yields, which is available in only a very few cases. For example, the ten years of yield history that is associated with an APH record would be far below the minimum that we would consider sufficient to estimate a statistically valid yield distribution. The RMA rating system uses the APH yield history to estimate the expected yield, but not the entire yield distribution.

In short, there are few cases where high quality farm yield series are available to support yield simulation based rating. Further, the best of yield series is almost always too short to adequately capture the effect of weather. Therefore, we are of the opinion that there are few, if any, instances where the data are adequate to support reliable yield simulation based rating.

Assumptions Regarding Non-Constant Yield Variability

Another important assumption that is troubling in the area of simulation based crop insurance rating is the issue of heteroskedasticity of the yield distribution. Heteroskedasticity is simply a statistical term that describes the possibility that the residuals in the regression context or the yield variability in the context of crop yields are not stable across time (or some other dimension). The work that has been done to date clearly suggests that assumptions about heteroskedasticity have a large effect on the rates derived from a simulation based rating approach (Woodard et al., 2009 and Harri et al., 2009a). Secondly, the evidence to support consistent assumptions about heteroskedasticity is lacking. In other words, the Harri, et al (2009a) paper clearly shows that it is possible to fail to reject heteroskedasticity and also fail to reject homoskedasticity in many data series. In some data series it is possible to draw statistical inferences about whether heteroskedasticity exists only to find out that with a few additional observations added to the time series the results change. It is our opinion that this is due to the fact that we are often examining heteroskedasticity in yield distributions without sufficient data. Ultimately we believe that in the context of simulation based rating reliable estimates would require the examination of heteroskedasticity on a case by case basis. And given sample sizes (time series length) of even 50, we would lack confidence that the appropriate assumption has been made.

Woodard et al (2009) examine the loss cost rating approach and conclude that a loss cost based system is exact only when risk increases proportionally with mean yields. They use farm-level data from the Illinois farm management record system to evaluate a simplified representation of the RMA procedures. The data used were for the 1980-2006 time period. They conclude the RMA assumptions are not likely to hold for Illinois corn.

The Woodard et al (2009) analysis and the Harri et al (2009a) both consider how yield variability may evolve with time or with changes in expected yield. However, neither controls for weather effects. As shown in the discussion of catastrophic loads, infrequent extreme losses often drive program rates in low risk regions. Thus, properly accounting for extreme weather events is essential for an accurate assessment of the RMA assumptions. Otherwise, a small sample can provide misleading results. We also note that various adjustments that RMA makes in the rating process alter the proportional risk assumption. For example, the catastrophic load procedure and the more recent Biotech Endorsement both modify rates from the simple historical loss cost approach.

To examine these issues we obtained the monthly total rainfall, mean temperature, and mean Palmer Drought Index for most states for the years 1950 to 2008. Similarly, we obtained state corn planted acre yields from 1950 to 2008 from the USDA/NASS database. With these data we investigate the RMA assumptions with a model that can control for weather.

Yield is modeled as a function of time to capture technology-driven changes in yields. Two alternative specifications are used. The first approach simply examines the residuals of a model with time trend where, y_t is the yield at time t as shown in equation 5.2. The second model (equation 5.3) controls for weather with the August Palmer Drought Index (PDI) and then tests for heteroskedasticity in the remaining unexplained variation in yield.

(Eq. 5.2) $$y_t = \gamma_0 + \gamma_1 t + \gamma_3 t^2 + \varepsilon_t$$

(Eq. 5.3) $$y_t = \gamma_0 + \gamma_1 t + \gamma_3 t^2 + \gamma_4 PDI + \varepsilon_t$$

Harri et al.(2009b) show that alternative forms of heteroskedasticity can be represented by the following relationship:

$$\sigma_t^2 = \sigma^2 [E(y_t)]^\beta = \sigma^2 \hat{y}_t^\beta .$$

The case of $\beta = 0$ indicates homoskedastic errors. When $\beta = 1$, then the variance of yields is proportional to the predicted (trending) yield. Finally, the case of $\beta = 2$ suggests that the standard deviation of yields moves in proportion to the predicted (trending) yield (i.e., that the coefficient of variation is constant). Given,

(Eq. 5.4)
$$E(y_t) = \alpha' x_t$$
$$\sigma^2 [E(y_t)]^2 = \sigma^2 (\gamma' x_t)^2$$

where the parameters γ of the variance equation are different from the parameters α of the mean equation. Then the following functional relationship holds:

(Eq. 5.5) $$\ln(\hat{e}_t^2) = \alpha + \beta \ln(\hat{y})$$

where $\hat{e}_t$ is the error term and $\hat{y}$ is the predicted value from a trend line.

The results of heteroskedasticity analysis are provided in Table 5.1. The values in this table reflect the β coefficient from the heteroskedasticity test (equation 5.5) estimated for corn and soybeans for various major production states. Corn data ends in 2005 to avoid the recent data affected by Bt technology for which RMA has now created a rate adjustment. The results are reported for each state/crop combination estimate, and with and without the PDI included in the equation to control for weather. While there is considerable variation in the estimated β across states, in 36 of the 38 models homoskedasticity is rejected. Further, if one statistically tests the β=2 assumption, it is not rejected in 32 cases. In the six cases where proportional risk is rejected only one (Wisconsin corn) is found to have a β less than 2.

These results are for a sample of crops and states that use data back to 1950. Ultimately, the question of proportional heteroskedasticity and RMA rating assumptions is an empirical one. In general, we conclude one should control for weather and use as many years of available data as possible to analyze the issue.

Table 5.1. Examination of Proportional Heteroskedasticity for Select Major Corn and Soybean States

Soybean			Corn		
State	**Without PDI**	**With PDI**	**State**	**Without PDI**	**With PDI**
IL	1.94	**2.81**	IL	**2.98**	**1.62**
IN	**5.28**	**2.49**	IN	**3.40**	**2.71**
IA	**1.99**	**2.07**	IA	**1.46**	**1.64**
KY	**1.91**	**1.33**	KY	**3.29**	**1.13**
MI	**1.80**	**2.64**	MI	**3.16**	**2.09**
MN	**2.21**	**2.48**	MN	**1.94**	**1.82**
ND	**1.61**	**1.64**	MO	**1.70**	**1.61**
OH	**3.51**	**2.50**	OH	**5.02**	**1.87**
WI	**1.64**	**2.47**	SD	**1.07**	**1.89**
(Bold indicates statistically significant at the 10% level			WI	**1.38**	1.01

Yield Data Challenges

In considering the possibility of using a relatively long yield series for a yield simulation based rating system, we think there are some very important caveats regarding the data. For example, we believe that it is very important to recognize whether the yields are taken from observations where the acreage was insured in each time period. The reason for this concern is that crop insurance may have an effect on producer behavior and yield outcomes. Unfortunately, it is unlikely that a long yield series will contain information on whether the acreage was insured and, if insured, at what coverage level. Thus, even with a long time series it is likely that essential information affecting yield and insurance outcomes will not be available.

It is also important to note that the level of aggregation reflected in the yield series is crucial. For RMA rating purposes what is needed is the ability to rate at the insured unit level, whatever level of aggregation may exist in that unit. So, we would strongly recommend that level of aggregation be taken into consideration. On a related note, the RMA does have a system in place which validates the accuracy of yield data when it is reported into the APH data system, and more so when an indemnity occurs and loss adjustment takes place. This gives a level of confidence in the crop insurance observed yields and loss experience that is greater than with alternative sources of yield data.

Behavioral Effects and Yield Data

While we do not attempt to quantify the degree to which adverse selection and moral hazard occur in the crop insurance program. It is well known that adverse selection (the fact that one will not always correctly categorize insured individuals) and moral hazard (the behavioral effect that results from having insurance coverage) are phenomena common to all property and casualty insurance. Crop insurance has safeguards such as deductibles which are deterrents to this type of behavior. However, to the extent that adverse selection and moral hazard occur in the crop insurance program, those behaviors are captured in the loss experience. That is, for example, if moral hazard behavior occurs its effects are reflected in the historical loss experience and will be a factor that influences future rates. To the extent that adverse selection and moral hazard have stable effects in the program, then they are priced into the crop insurance premium rates as they would be in any property and casualty line that uses loss experience. It would be very difficult to incorporate behavioral effects of this type in a yield simulation model unless one has explicit information about behavior which is seldom if ever available.

6.0 Evaluation of the APH Rating System and Suggestions for Consideration

In the course of our review of RMA's current rating procedures we identified several issues warranting further analysis. In this chapter we discuss those issues and the results of the analysis that was done within the scope of the current review. Our analysis of some of these issues alleviated our concerns. On other issues it led to suggestions for potential refinements to the rating procedures. Most of the suggested refinements would require some modifications of the Statplan database and all would require at least modest changes to computation procedures. Some suggested changes would require in-depth studies to develop rating factors for specific crops and regions. Finally, one of the refinements we recommend for further evaluation constitutes a significant departure from the current loss cost ratio based rating procedures. Given the scope and overall programmatic implications of this change we believe that extensive analysis would be needed prior to implementation. As we discuss each potential refinement we also offer our assessment of challenges the change would pose in implementation.

6.1 Basic Approach to APH Rating

Based on our review of the fundamentally challenges of crop insurance rating that were discussed in Chapter 5 we believe that it is clear that RMA should continue to use loss experience rather than simulation-based models. ***We recommend that RMA continue to use loss experience as the foundation of the rating system as it is the only way to assure that actual losses drive the rating results. This is consistent with standard property and casualty insurance rating practices. While crop insurance poses a unique set of actuarial challenges, alternatives to loss-experience-based rating would likely fail to adequately address the multiple objectives imposed on the APH program.***

6.2 Reference Rate, Reference Yield and Exponent

The reference rate, reference yield and exponential yield ratio curve are closely connected. The reference rate (county ULR with reserve factor load applied) is the variable portion of the premium rate charged for an insured unit with rate yield equal to the reference yield (i.e., yield ratio of 1.0). As discussed in section 4.2 above, the variable portion of rates for insured units with rate yields below the reference yield are higher than the reference rate while rates for units with rate yields above the reference yield are lower than the reference rate. These rate differentials are determined by the yield ratio rating curve, the shape of which is determined by the exponent discussed in section 4.3. We find two concerns about the validity of reference rates as applied in conjunction with the reference yield. The first is whether the reference rate and reference yield are developed in a congruent manner and the second is whether the reference yield is biased upward due to convexity of the yield ratio curve. Here we discuss these concerns and also examine issues relating to the yield ratio curve and exponent.

Connecting Reference Rates and Reference Yields

As discussed in section 4.2, two different bodies of data are used in calculating the county reference yield and reference rate. Reference yields were initially based on NASS county yields. They are now periodically adjusted based on updated county T-yields. County reference rates are based on average capped loss cost experience for insured units with varying yield ratios. Given these procedures, there is no assurance that the reference rate for a county is appropriately centered on the reference yield. This potential problem is illustrated in Examples 1 and 2 in table 6.1. These examples make use of the 2009 rating parameters for corn in Boone County, Iowa. These parameters are: reference yield=150, reference rate=0.015, exponent=-2.051, fixed rate load=0.008.

Table 6.1. Example Reference Rate Calculations for Insured Units with Different Patterns of Rate Yields Relative to the Reference Yield

Example 1		Example 2		Example 3	
Rate Yields	Implied Loss Cost Ratio	Rate Yields	Implied Loss Cost Ratio	Rate Yields	Implied Loss Cost Ratio
100	0.042	150	0.023	100	0.042
105	0.039	155	0.022	110	0.036
110	0.036	160	0.021	120	0.032
115	0.034	165	0.020	130	0.028
120	0.032	170	0.020	140	0.025
125	0.030	175	0.019	150	0.023
130	0.028	180	0.018	160	0.021
135	0.027	185	0.018	170	0.020
140	0.025	190	0.017	180	0.018
145	0.024	195	0.017	190	0.017
150	0.023	200	0.016	200	0.016
Average	0.031		0.019		0.025

Example 6.1 illustrates what would occur if all of the expected insured rate yields in a county in a given year were at or below the reference yield. Here the eleven yields used range from the reference yield of 150 bushels per acre down to 100 bushels per acre, in five bushel increments. The loss cost ratio for each unit is calculated under the assumption that the realized loss experience is exactly equal to the insured's expected

yield and therefore consistent with what is implied by the rates. For example, the loss cost ratio for a unit with a particular rate yield is assumed to be exactly equal to the associated premium rate. For simplicity, we also assume that equal liability is insured at each yield level. Given these assumptions, the average loss cost ratio is 0.031. This is 35% higher than the county's implied loss cost ratio of 0.023 at the reference yield. What this means is that if the loss experience in a county is weighted toward yields that are below the reference yield the average loss cost ratio, in this case 0.031, will be substantially higher than the appropriate premium rate for an insured unit with rate yield equal to the reference yield of 150 bushels per acre. If this loss cost ratio is applied to units with rate yields equal to the reference yield then the rates are biased upward. [Note: To simplify this illustration we have not censored the loss cost ratios at the 80th percentile.]

Example 2 illustrates the opposite situation—all of the expected insured yields are at or above the reference yield. In this case the actual expected loss cost ratio of 0.019 is substantially (16%) below the expected loss cost ratio (0.023) and fair premium rate for an insured unit with rate yield equal to the reference yield. The implication of this is that if the loss experience in a county is weighted toward yields that are above the reference yield the average loss cost ratio, in this case 0.019 will be substantially lower than the appropriate premium rate for an insured unit with rate yield equal to the reference yield. If this loss cost ratio is applied to units with rate yields equal to the reference yield then the rates are biased downward.

Examples 1 and 2 above clearly show the importance of proper alignment of reference rates with reference yields. The 2003 Reference Yield Update Methodology report cited earlier in section 4.2 suggested that at that time reference yields were biased downward compared with APH yields of insured units. Specifically, the study showed that for the following major crops average APH yields of insured units exceeded associated county reference yields by the following average percentages: wheat 19%, cotton 13%, sugar beets 15%, corn 25%, sweet corn 15%, soybeans 21%, and potatoes 11%.[13] Based on the relationships illustrated in table 6.1 and discussed above, this pattern of APH yields substantially higher than county reference yields would bias reference rates downward compared to the "correct" rate for the reference yield. It should be acknowledged that updates to reference yields since 2003 may have substantially changed these relationships. However, the Reference Yield Updating Methodology report recommended that the RMA adopt procedures for using recent rate yields of insured units in a county and, where needed to satisfy data credibility standards, for surrounding counties, in computing county reference yields. ***We recommend RMA adopt updated reference yields which are congruent with reference rates and exponents, a critical step in obtaining appropriate rates for insured units at all yield levels. These updated***

[13] The reported values reflect national averages. Significant regional differences in these values were identified in the report.

reference yields would be based upon APH data so that the reference yield and reference rate are 'centered' within a county's book of business.

Another issue regarding reference rates and reference yields that warrants consideration is illustrated in Example 3. In this example, the insured rate yields are uniformly distributed around the reference yield. Thus, there is no weighting of liability either above or below the reference yield. Even in these circumstances, with the reference yield centered on the rate yield to which the reference rate applies, we find a potential bias in the loss-cost ratio based reference rate. This bias arises due to the convexity of the yield ratio curve. Given a convex function relating expected loss costs to reference rates it is well known that due to Jensen's inequality the average loss cost in Example 3 will be higher than the expected loss cost ratio for a unit with rate yield equal to the average for the county. The reason for this is that, with a convex yield ratio function, "surcharges" for units with rate yields above the reference yield are larger than "discounts" for units with rate yields that are an equal distance below the reference yield. The point is that the average loss-cost-ratio based premium rate may be biased upward due to convexity of the yield ratio relationship, even if insured liability is uniformly spread around the reference yield. The average loss cost ratio in Example 3 is 0.025, which is 10% higher than the appropriate rate for an insured unit with rate yield equal to the reference yield.

The 2003 Reference Yield Methodology report addressed the potential problem of rate bias due to the convexity of the yield ratio curve. Two approaches were used to analyze the issue. One approach assumed that the current "exponential rate curve for each county is accurate (i.e., that it accurately reflects differences in expected loss cost ratios for insured units with different yield ratios). This curve and other rating parameters were applied to the actual rate yields for units insured in 2003 to obtain the implied loss cost ratios for each unit. The second approach involved calculation of "the 13-year loss costs for each crop/type/practice in each county in two ways: (1) using data for all insured units; and (2) using just data for units with updated yield ratios (yield ratios based on updated reference yields) that are ―near 1.0 (specifically from 0.9 to 1.1)." The all-data county loss cost ratio was divided by the restricted-data loss cost ratio "to determine how well averaging across all data represents the loss cost experience for insured units with yields near the reference yield." This analysis was conducted for corn, cotton, soybeans and wheat. The results of this analysis led the authors to conclude that the convexity effect is modest in magnitude (less than 5% to 7%). It is our opinion that correcting for this modest potential bias would substantially increase the Statplan data and analysis requirements. We do not believe the rate accuracy gained would justify the costs associated with these additional data and analysis requirements. Therefore, we do not recommend changes to the reference rate development procedures to address this small potential bias.

Yield Ratio Curve and Exponent

Assuming that the reference rate and reference yield are derived in a consistent manner the yield ratio curve is used to adjust rates for producers with different rate yields. As discussed in section 4.3, it is our understanding that the exponents currently used to determine the shape of the yield ratio curve are based on relationships that were in use prior to implementation of the continuous rating system in 2001. Given that, we recommend that RMA update these exponents. The 2008 internal memo discussed earlier identifies statistical relationships, related to sampling error in average (rate) yields and regression to the mean, which could potentially give rise to yield ratio relationships that are "flatter" than those produced by the current exponents. The memo proposes updating the exponents using nonlinear least squares (NLS) to estimate insured unit level loss cost ratios (*LCRs*) as follows:

(Eq. 6.1) $$LCR = \beta_0 \times \left[\frac{APH_i}{APH}\right]^{\beta_1} + \varepsilon \,.$$

We agree with the explanation provided in the memo regarding a conceptual basis that could lead to flatter yield ratio relationships. We would restate the estimation equation as follows to clarify that the rate yield rather than the APH yield for an insured unit should be used in the numerator and the reference yield in the denominator:

(Eq. 6.2) $$LCR = \beta_0 \times \left[\frac{Rate\,Yield_i}{Reference\,Yield}\right]^{\beta_1} + \varepsilon \,.$$

We also believe there is merit in using a censored regression model due to the nature of the dependant variable. (See, for example, Stute, 1999 and Chay and Powell, 2001).

Based on our review of the yield ratio curve and the rating exponent we recommend that RMA conduct analysis to update these parameters of the rating formula. Given the heavy censoring of loss cost ratios at zero we suggest that the RMA investigate the use of a censored regression model for the estimation.

6.3 Type and Practice Factors

Procedures for developing type/practice factors were summarized in section 4.4. It is our opinion that the approach used by the RMA in developing these factors is reasonable. The non-censored loss cost ratio for each type/practice combination in a region is divided by the non-censored, combined loss cost ratio for all types and practices in the region to obtain a raw TpFactor. These raw factors are weighted by county type/practice liability proportions over the full rating period and normalized to obtain final county TpFactors. These final factors have the property of collecting the same amount of premium as would be collected if the simple average loss cost ratio for the county (combining all types/practices) were multiplied by total county insured liability. That is, with no censoring of the data, use of these final type/practice rating factors distributes premium rates to types/practices combinations in a way that collects the same amount of premium as would be collected if the combined (across all type/practices) loss cost ratio were used as the premium rate and multiplied by total liability for the rating period.

Although we consider the general type/practice factor development procedures reasonable, we have one major concern about an inconsistency between how the factors are developed and how they are applied. As indicated above and shown in section 4.4, the type/practice factors are constructed in a way that distributes total premium to type/practice combinations while collecting an amount of total premium consistent with expected losses, as measured by the raw combined type/practice loss cost ratio for the county. This balance between premium collected and expected losses is achieved using the county non-capped loss cost ratio as an implicit "all type/practice" rate to which the TpFactors are applied. However, as shown in equation 6.3 below (repeated from section 4.1 (equation 4.2)), when rating an insured unit the TpFactors are only applied to a portion of the rate. Importantly, the State Catastrophic Rate Load is not included in the part of the rate that is multiplied by the TpFactors. It is our opinion that this is inconsistent with the way the TpFactors are developed and that the result is type/practice rates that are likely biased downward for higher cost types/practices and upward for lower cost types/practices. Whether the TpFactors should be applied to the prevented planting (PP), replant, and quality adjustment (QA) rate components is less clear. For example, prevented planting indemnities and associated liability are excluded from the production ratio calculations underlying the target county rates. The same is true of indemnities that are paid to insured producers to cover the cost of replanting. Further, it is not clear that rates associated with these causes of loss should be distributed to crop types/practice combinations in the same way as production losses.[14]

(Eq. 6.3) Target Rate for Individual =

$$\left[\left(\left(\frac{\left(\frac{\left(\mathrm{ULR}\times(\mathrm{Ry})^{-E}\right)+\mathrm{CntyCAT}}{\mathrm{ResFac}}\right)}{\mathrm{UnitFac}}\right)\times\mathrm{TpFactor}\right)+\left(\frac{\mathrm{PP}+\mathrm{RP}+\mathrm{QA}+\mathrm{StCAT}}{\mathrm{UnitFac}}\right)\right]\times\mathrm{CLD}\,.$$

[14] We should also note that proper allocation of these rate factors to crop types and practices likely varies significantly by crop and region. Here we use prevented planting as an example. In some regions, such as the Midwest, a primary cause of prevented planting losses is excess moisture. This would likely have similar effects on both corn types (corn for grain and corn for silage). However, in an area where inadequate moisture is a significant cause of prevented planting losses the effect could vary greatly between irrigated and non-irrigated planting practices.

Our main point is that type/practice factors are developed in a way that is structured to balance premiums collected with expected losses (as measured by the combined type/practice loss cost ratio for the rating period). However, inconsistencies between the way these factors are developed and how they are applied create a risk of premium inaccuracies between types and practices.

Although the current process results in a balanced collection of revenue, it also results in separate type/practice factors for every county, making it appear that the type/practice differentials are somehow different by county. If the same calculations currently used to adjust regional type/practice factors were instead used to adjust the county base rate to a single practice level, then a single set of regional type/practice factors could be applied in every county. Moreover, if one type/practice were selected as the base and assigned a factor of 1.00, then type/practice differentials would be more easily comparable across time and across regions.

Beginning with Step 2 in our example from Section 4.4:

(4.4alt)
$$RF_{R1} = 1.00$$
$$RF_{R2} = \frac{SALC_{R2}}{SALC_{R1}}$$

Step 3: (4.5alt)
$$Extension_{C} = LW_{C1} + LW_{C2} \times RF_{R2}$$

Step 4: Calculate the adjusted base rate for the county, which is the rate for type/practice 1:

(4.6alt)
$$ABR_C = \frac{SALC_{CT}}{Extension_C}$$

The total premium collected still balances:

(4.7alt)
$$Premium_{Cj} = RF_{Cj} \times ABR_C \times Liab_{Cj}$$

(4.8alt)
$$\begin{aligned} Premium_{CT} &= Premium_{C1} + Premium_{C2} \\ &= ABR_C \times Liab_{C1} + RF_{R2} \times ABR_C \times Liab_{C2} \\ &= \frac{SALC_{CT}}{(LW_{C1} + LW_{C2} \times RF_{R2})} \times (Liab_{C1} + RF_{R2} \times Liab_{C2}) \\ &= \frac{SALC_{CT}}{(\frac{Liab_{C1}}{Liab_{CT}} + \frac{Liab_{C2}}{Liab_{CT}} \times RF_{R2})} \times (Liab_{C1} + RF_{R2} \times Liab_{C2}) \\ &= SALC_{CT} \times Liab_{CT} \times \frac{(Liab_{C1} + RF_{R2} \times Liab_{C2})}{(Liab_{C1} + RF_{R2} \times Liab_{C2})} = SALC_{CT} \times Liab_{CT} \end{aligned}$$

Based on our analysis we recommend that the RMA modify its procedures so that the TpFactors are applied to the State Catastrophic Rate Load portion of the target rate. Further, we recommend that RMA rebase its rates and type/practice factors to a common type/practice to improve the transparency of the rating structure.

Using Liability Weights Based on More Recent Experience

In its internal type/practice guidelines document the RMA recognized that a problem may exist in its type/practice rating procedures when the type/practice mix changes significantly over the rating period. In this case the county type/practice liability weights and the county simple average loss cost for the rating period may not be reflective of current liability proportions and future expected losses.

The method currently used by RMA to set and apply type/practice factors, even if adjusted to simplify the resulting rate structure as suggested above, is still dependent on the assumption that the distribution of liability across types/practices has not changed materially throughout the experience. Clearly, this is not always the case and assuming that producers shift to more productive/less risky types and practices over time results in an upward bias on the base rates. To illustrate how changes in mix affect the indicated base rates, we extend the previous example. Consider a crop with two production practices, with a constant differential in experience between the two practices. Practice 2's expected losses are twice those of practice 1, and in our example, the actual experience exactly equals the expected. The proportion of producers electing practice 1 has been steadily increasing:

Table 6.2. Example Experience for a County with a Shifting Mix by Practice

Year	Practice 1 Liability	Practice 2 Liability	Practice 1 Indemnity	Practice 2 Indemnity
1	300,000	700,000	30,000	**140,000**
2	400,000	600,000	40,000	**120,000**
3	500,000	500,000	50,000	**100,000**
4	600,000	400,000	60,000	**80,000**
5	700,000	300,000	70,000	**60,000**
Total	**2,500,000**	**2,500,000**	**250,000**	**500,000**

$$SALC_{R1} = 10\% \text{ and } SALC_{R2} = 20\%$$

Note that the SALC by practice has not changed over time.

The SALC for the county is then:

Table 6.3. Example County Experience: All Type and Practices Combined

Year	Liability	Indemnity	Loss Cost Ratio
1	1,000,000	170,000	**17%**
2	1,000,000	160,000	**16%**
3	1,000,000	150,000	**15%**
4	1,000,000	140,000	**14%**
5	1,000,000	130,000	**13%**
SALC for the county = All year average			**15%**

The indicated type/practice differentials and total premium are then:

$$RF_{R1} = 1.00 \text{ and } RF_{R2} = \frac{20\%}{10\%} = 2.00$$

$$LW_{C1} = 70\% \text{ and } LW_{C2} = 30\%$$

$$Extension_C = 70\% + 30\% \times 2.00 = 1.30$$

$$ABR_C = \frac{15\%}{1.3} = 11.5385\%$$

Assuming that the liability in year 6 is the same as in year 5, then the premium collected will be:

$$Premium_C = 700,000 \times 11.5385\% + 300,000 \times 11.5385\% \times 2.00 = \$150,000$$

Expected indemnity, however, is $130,000.

Where the distribution across practices in the history is known, the appropriate adjustment is straightforward, and simply requires substituting the current liability distribution:

Table 6.4. Adjusting the Historical Weighting by Practice to the Current Distribution

Year	Prac 1 L/R	Prac 2 L/R	Weight to Prac1	Adjusted L/R
1	10%	20%	70%	**13%**
2	10%	20%	70%	**13%**
3	10%	20%	70%	**13%**
4	10%	20%	70%	**13%**
5	10%	20%	70%	**13%**
SALC				**13%**

$$ABR_C = \frac{13\%}{1.3} = 10\%$$

Assuming that the liability in year 6 is the same as in year 5, then the premium collected will be

$$Premium_C = 700,000 \times 10\% + 300,000 \times 10\% \times 2.00 = \$130,000$$

In cases where the liability distribution by type/practice cannot be determined for the whole history, a reasonable approximation would be to assume that the oldest available distribution holds for the prior years. If it is clear that there was significant evolution in the distribution even in the oldest time period for which data are available, earlier distributions could be extrapolated, using appropriate judgment. If a particular type/practice was introduced after the start of the APH time series, the distribution percentage for the new type/practice is set to 0% for prior years. We also must make an assumption about the relative experience of the various types/practices, and again it is reasonable to assume that the relative experience in the oldest few years with available data can be extrapolated backwards. Extending our example a bit further, suppose that there is actually 10 years of experience for our county, but only total county experience is available prior to year 1, and moreover that there were some years with dramatically different experience in the prior period:

Table 6.5. Extending the Example County Experience to 10 Years

Year	Liability	Indemnity	Loss Cost Ratio
-4	1,000,000	500,000	**50%**
-3	1,000,000	200,000	**20%**
-2	1,000,000	400,000	**40%**
-1	1,000,000	190,000	**19%**
0	1,000,000	180,000	**18%**
1	1,000,000	170,000	**17%**
2	1,000,000	160,000	**16%**
3	1,000,000	150,000	**15%**
4	1,000,000	140,000	**14%**
5	1,000,000	130,000	**13%**
SALC for the county = All year average			**22.2%**

Given the observed shift in liability weights, it is appropriate to assume that the mix was shifting prior to the observed data, but perhaps somewhat more slowly (a conservative assumption). We assume that the 2:1 experience ratio applied for the prior years.

Table 6.6. A Reasonable Estimate of the Split by Practice for the Older Years

Year	Practice 1 Liability	Practice 2 Liability	Practice 1 Indemnity	Practice 2 Indemnity	Practice 1 L/R	Practice 2 L/R
-4	50,000	950,000	12821	487,179	25.6%	**51.3%**
-3	100,000	900,000	10526	189,474	10.5%	**21.1%**
-2	150,000	850,000	32432	367,568	21.6%	**43.2%**
-1	200,000	800,000	21111	168,889	10.6%	**21.1%**
0	250,000	750,000	25714	154,286	10.3%	**20.6%**
1	300,000	700,000	30,000	140,000	10.0%	**20.0%**
2	400,000	600,000	40,000	120,000	10.0%	**20.0%**
3	500,000	500,000	50,000	100,000	10.0%	**20.0%**
4	600,000	400,000	60,000	80,000	10.0%	**20.0%**
5	700,000	300,000	70,000	60,000	10.0%	**20.0%**
SALC by practice					**12.9%**	**25.7%**

Restating the old experience under the current weights gives us:

Table 6.7. Adjusting the 10 Years of Experience to Reflect the Current Distribution by Practice

Year	Prac 1 L/R	Prac 2 L/R	Weight to Prac1	Adjusted L/R
-4	25.6%	51.3%	70%	**33.3%**
-3	10.5%	21.1%	70%	**13.7%**
-2	21.6%	43.2%	70%	**28.1%**
-1	10.6%	21.1%	70%	**13.7%**
0	10.3%	20.6%	70%	**13.4%**
1	10%	20%	70%	**13%**
2	10%	20%	70%	**13%**
3	10%	20%	70%	**13%**
4	10%	20%	70%	**13%**
5	10%	20%	70%	**13%**
SALC				**16.7%**

We have accounted for the change in the mix of business while continuing to capture the fact that, even with different type/practice weighting, the experience in prior years was significantly poorer than in more recent years.

Premiums for year 6 are then:

$$ABR_C = \frac{16.7\%}{1.3} = 12.863\%$$

$$Premium_C = 700,000 \times 12.863\% + 300,000 \times 12.863\% \times 2.00 = \$167,000$$

We recommend that RMA adjust prior experience for the actual or estimated mix by type and practice.

6.4 Adjustments for Unit Structure

In Chapter 3 we discussed how the historical loss experience is adjusted in developing the county target rate. Revenue product liability and indemnity are adjusted to reflect yield-based loss experience. Additional adjustments approximately normalize the experience to a common 65% coverage level. These adjustments are made to obtain a consistent dataset for rate computation. However, there are no similar adjustments to the data to reflect differences in unit structure. In this section we examine the implications of not adjusting for unit structure in developing county target rates.

Equation 6.5 below, is repeated from section 4.1 (equation 4.1) for convenience. It is the expression for the county target rate. The unit factor (UnitFac) used in this equation is 0.9. The implication of this is that all of the rating parameters in the numerator are treated as though they represent basic unit loss experience. Dividing by UnitFac=0.9 effectively surcharges these rates up to the level treated as appropriate for optional units. When the rates are published in the actuarial documents the multiplicative rating factor for optional units is 1.0, indicating that the published reference rate and fixed rate load are for optional units. A multiplicative unit factor of 0.9 is used to provide a 10% discount for basic units.

(Eq. 6.5) $$\text{Target Rate} = \left(\frac{\left(\frac{\text{ULR+CntyCAT}}{\text{ResFac}} \right)}{\text{UnitFac}} \right) + \left(\frac{\text{PP+RP+QA+StCAT}}{\text{UnitFac}} \right)$$

It is our opinion that this treatment of unit structure in the rating process is problematic because loss experience for all unit formats (optional, basic, and enterprise) is treated as though it were for basic units. In reality, a significant part of the experience since the late 1980s has been for optional units and a relatively small amount of experience, primarily on CRC and RA, is for enterprise units. Treating the experience for optional units as though it were for basic units and surcharging it up in obtaining a county target rate assumed applicable for optional units has the effect of adding an additional load to the optional unit loss experience contained in the loss history (the opposite is true for the relatively small proportion of enterprise units with rating factors less than 0.9). If all of the historical experience was for basic units, and the current 10% discount factor was appropriate for basic versus optional units, then this process would be correct. The experience would be surcharged up to the optional unit level and then discounted by 10% for units insured as basic units. Conversely, if all of the experience was for optional units the target rate, applicable for optional units, would be 11.1% higher than appropriate. This would result in rates that are too high for both optional and basic units. A possible correction to this process reflecting mixed basic and optional unit experience in a county would be:

$$UnitFac = Proportion\ Optional \times 1.0 + Proportion\ Basic \times 0.9$$

where *proportion optional* and *proportion basic* are the proportions of total county insured liability on optional and basic units, respectively. This adjustment should be correct when applied to the ULR, CntyCAT, and StCAT portions of the target rate. It is less clear whether the adjustment is correct for the PP, RP, and QA portions of the rate because it is not clear whether unit structure rate differentials are appropriate for these rate components. Further, even if unit structure rate differentials are appropriate for these rate components, the appropriate differentials may vary by component. However, the PP, RP, and QA rating components are generally small in magnitude compared with the ULR, CntyCAT, and StCat. Thus, with just basic and optional units in a county, the above process should closely approximate the appropriate target rate for the county.

The above process addresses the problem of counties with mixed basic and optional unit experience. However, it does not address the variable discounts for enterprise units which are becoming more important due to larger subsidies for this unit structure provided in the 2008 Farm Bill and the significant shift to enterprise units that has occurred. Given a substantial shift in the book of business to enterprise units, an appropriate adjustment process for the variable discounts associated with this unit format would be needed. A factor analogous to the above factor for basic and optional units is:

$$UnitFac = \sum_i^n Proportion_{Fi} \times F_i \ ,$$

where F_i is one of a range of proportionate discount factors and $Proportion_{Fi}$ is the proportion of liability in the county to which the discount factor F_i applies. For example, if a county had 50% of liability in optional units with a discount factor of 1.0, 30% of liability in basic units with a discount factor of 0.9, and 20% of liability in enterprise units with a discount factor of 0.8, then UnitFac used in equation 7.5 above would be:

$$UnitFac = 0.5 \times 1.0 + 0.3 \times 0.9 + 0.2 \times 0.8 = 0.93\ .$$

The above process is straightforward. However, we recognize that the primary difficulty posed is that a large number of enterprise unit discount factors may be used for different insured units in a county (the same will be true of basic units when the results of the Unit Structure study are applied). In order to implement the process it would be necessary to maintain in Statplan records of liability in each county to which each discount factor applies in each year. The rounding of discounts to a manageable set of discrete factors might be useful in simplifying this process. Even if the actual discounts were not rounded, it might be judged acceptable to round the factors maintained in Statplan at say 5% increments so that the number stored would be relatively modest. This compromise in the interest of ease of data management would introduce approximation error but would be superior to the current process which is subject to substantial error when larger enterprise (or basic) unit discounts are applicable for a substantial proportion of liability in a county. **We recommend that RMA adopt procedures for developing target rates that incorporate unit factors that are consistent with the mix of unit structures in the historical loss experience.**

6.5 Coverage Level Adjustments

Rates are currently set at the 65% coverage level. Other coverage levels are rated by applying a factor to the 65% rate. Coverage level factors are periodically adjusted through special studies that are not part of the base rate setting process.

Data for other coverage levels are adjusted to a 65% equivalent. The adjustment from higher coverage levels (e.g. from a 75% level to a 65% level) is appropriate and accurately captures the change because all indemnity under a 65% coverage level is captured within the 75% indemnity. This is not the case, however, when the actual coverage level in the data is less than the target 65% level. The missing data are indemnity for producers with production ratios between the actual coverage (e.g. 50%) and the base 65% level. Because no coverage was provided at the lower level, actual production is not captured in the database, making it impossible to calculate what the actual losses would have been had the producer elected 65% coverage. RMA estimates the missing indemnity by selecting an average between the maximum and minimum possible outcomes, where the minimum assumes that no producers had production percentages between the lower coverage level and 65% and the maximum assumes that all producers without indemnity losses had actual production just above the actual coverage level. When this estimation approach was adopted a number of years ago, the percentage of business at coverage levels below 65% was very small, and the averaging method in most cases would not have had a material effect on the result. However, some crop/region combinations have a significant proportion of producers below 65% coverage, resulting in more weight given to an ad hoc adjustment procedure.

Neither adjustment (from higher coverage to 65% or from lower coverage to 65%) captures differences in insured population or insured behavior at different coverage levels. As has been discussed, there is evidence that, as the coverage level increases, the opportunity for moral hazard effects increases. Thus, adjusting from a higher coverage level to a lower coverage level may overstate the adjusted experience. It is difficult to assess whether the adjustment from lower coverage levels to the base level overstates or understates the appropriate adjustment for producer behavior.

If the base coverage level were, instead, set at the 50% level, it would not be necessary to manufacture missing indemnity data. It is typical in property/casualty ratemaking either to set the base coverage level at the largest deductible (lowest coverage level) with a significant percentage of insureds or to set separate rates by deductible. Setting separate rates by coverage level requires credible volumes of data at each coverage level, which is not practical for the RMA system. However, changing the base deductible for pure premium calculation purposes to the 50% coverage level would be a simple modification that would eliminate the need to guess at a potentially large volume of missing indemnity data. We believe the error due to approximation outweighs the statistical error associated with lower coverages identified by Ker and Coble (1998).

We are left, then, with the possible need to reflect the effect of variances in producer behavior across coverage levels in the base rate. Coverage level adjustment factors are appropriately estimated through studies that compare actual experience at different coverage levels for recent experience over a wider aggregation of data than the county level. It would be possible, using the same set of data, to calculate coverage level adjustment factors based on the effect of adjusting the experience to the lowest coverage level, which captures only the difference in liability and indemnity assuming consistent producer behavior. It is likely that the results of the latter calculation (the same calculation used in setting the base rate) will produce smaller coverage level differentials than the actual experience indicates. The difference in the two sets of differentials is a reasonable estimate of the behavior effect and if significant could be reflected through a reduction in the base rate

We recommend that RMA eliminate the coverage approximation procedure and adjust all experience to the 50% coverage level when low coverage levels make up a significant proportion of experience. Published base rates could still be maintained at the 65% coverage level, simply by dividing the 50% pure premium by the 50% coverage level adjustment factor. We recognize this would place greater reliance on the estimated coverage level relativities. However, we believe these can be effectively estimated in the major crops.

6.6 Catastrophic Loading

The current catastrophe loading methodology removes indemnity above the 80th percentile from the county experience and spreads it across the entire state. Most of the catastrophic load is spread through an additive of up to .0325, while any remaining catastrophe load is spread in proportion to each county's excess indemnity. This methodology assumes that the potential for catastrophe (or at least the potential for moderate catastrophes up to the cap) is not affected by the actual county experience. The result is, on a percentage basis, a much bigger loading for catastrophes in counties with better non-CAT experience than in counties with poorer non-CAT experience. Milliman has performed a comprehensive evaluation of the RMA CAT loading process (Milliman, 2008), concluding that there are several potential changes to the process that would improve the efficiency ratio. We concur with the Milliman and Robertson review. ***We recommend that RMA re-evaluate the catastrophic loading procedure and reduce the degree to which CAT loading influences rates in low risk regions. Having said this, we generally support maintaining state/crop catastrophic loading boundaries, unless one is addressing a crop with geographically-sparse participation.***

6.7 Use of Expert Judgment

Where data are sparse, expert judgment is inserted into the ratemaking process to ensure that the resulting rates are logical. The ratemaking process also allows for expert judgment intervention where there is significant credible data. It is not clear to us under what circumstances such an intervention is permitted, and even allowing for such adjustments may lead to the perception that the ratemaking process unfairly selects certain crops or areas for special treatment. ***We recommend that if, in fact, local conditions have changed such that an existing credible time series of data is not appropriate for rating, an explicit discussion of the changes should accompany a plan to either adjust the prior data or to set a rate through judgment that will then be adjusted using standard methods as new data accumulate. Regional offices of the RMA should play a role in any such process. The decision and results should be documented, transparent, and reviewable by outside parties.***

6.8 Additional Rating Variables

Actual producer experience is likely to be significantly influenced by both physical farm characteristics and production methods. The producer's actual production history, if available, serves as a proxy for the collective effect of all such characteristics, filtered through the overlay of weather and other environmental effects and producer choices (moral hazard effects). In the days when data gathering and storage posed significant cost issues, it was appropriate to limit the number of rating variables considered. In today's environment, however, such limitations on data should no longer impose significant barriers. We note that recent advances in property/casualty ratemaking include a significant increase of the number of potential explanatory variables considered. It may be the case that a significant amount of the county-to-county variation in rates may be explained by differences in soil types, elevation, slope, production systems employed, and other data that should be readily collectible and either stable across time or with changes that can be documented. It is reasonable to assume that the number of coverage options will only continue to increase, resulting in the need for finer and finer rating variables. We recognize that site-specific information is a significant advancement from where the program is today. However, a pilot project could examine the logistics of such a system. ***We recommend a comprehensive study evaluate utilizing soil and other site specific information. We also suggest RMA consider defining and collecting additional type and practice data for characteristics that likely affect insurance risk levels.***

6.9 Statewide Rate Level Adequacy

The methods employed to limit the effect of rate changes on individual producer rates are asymmetrical. That is, they move actual rates toward indicated levels much more quickly on the downside than on the upside. If a significant number of producers are affected by rate capping, the result can be overall rate inadequacy even when the published base rate is actuarially sound. There is no mechanism in the rating process to test whether the actual premiums collected meet the mandate that premium shall be sufficient to cover anticipated losses and a reasonable reserve. In cases where the statewide premiums prior to the application of the reserve factor are significantly short, it may be appropriate to increase the reserve factor and/or add a rating off-balance load to uncapped rates. In the other direction, the catastrophe minimum load of 0.0065 may in some instances produce a statewide premium that is in excess of the mandated level. ***We recommend that RMA evaluate the extent to which statewide rate levels may be inadequate due to capping and, if significant, consider the use of an inadequacy off-balance. We recommend that RMA consider re-evaluating whether the minimum load is appropriate in light of the additional reserve loading.***

6.10 Catastrophic Coverage Rates

RMA currently treats the catastrophic coverage policy as a comparable unit of insurance to any other policy, and the premium rates that are offered on catastrophic coverage are identical to the premium rates that are offered on a 50/100 policy. We evaluated whether the premium rates for the catastrophic coverage policy appeared to be consistent with those for other coverages. Note the following language applied to the catastrophic coverage policy:

> ***Unit Division***
> *(a) This section is in lieu of the unit provisions specified in the applicable crop policy.*
> *(b) For catastrophic risk protection coverage, a unit will be all insurable acreage of the insured crop in the county on the date coverage begins for the crop year:*
> *(1) In which you have one hundred percent (100%) crop share; or*
> *(2) Which is owned by one person and operated by another person on a share basis. (Example: If, in addition to the land you own, you rent land from five landlords, three on a crop share basis and two on a cash basis, you would be entitled to four units; one for each crop share lease and one that combines the two cash leases and the land you own.)*
> *(c) Further division of the units described in paragraph (b) above is not allowed under this Endorsement.*

Thus, the catastrophic coverage policy is defined essentially as a basic unit. However the reduced price election serves as a co-payment on this policy. To analyze the potential differences between the pool of catastrophic coverage losses versus non-catastrophic coverage policies, we utilized the RMA summary of business data from 1995 through 2008. These data sets report the loss experience on a county-by-county basis for various coverage levels and allow one to identify both the coverage level and whether it was a catastrophic coverage policy or a buy-up policy. We aggregated these data across the 1995-2008 period and looked at the observed loss cost ratios for policies that were the APH insurance plan and at the 50 percent coverage level. Thus, the experience that we examined is experience for both the 50 percent coverage buy-up policies and 50 percent coverage catastrophic policies.

To evaluate the relative loss experience, we aggregated the data by crop, state, and year. So, for example, we conducted a comparison of 50 percent coverage corn APH policies in Indiana in 2005. We compare the loss cost ratios observed for catastrophic coverage policies versus the loss cost ratios observed for the non-CAT 50 percent coverage policies and computed a ratio of the catastrophic loss cost ratio to the buy-up loss cost ratio. In the case where the actuarially fair rates for CAT policies and buy-up policies were identical, the expected ratio would be 1.0. In our analysis we also limited a minimum level of liability to be $1,000 in a county to avoid thin data counties. We conducted the analysis and then aggregated the average values that we observed to the national level for seven crops. These are reported in Table 6.8. For example, for wheat we had 599 state year combinations. The average ratio that we observed was 0.638. This indicates that wheat catastrophic coverage in the same year, in the same state, had a loss cost ratio that was roughly 64 percent of the loss cost ratio for buy-up coverage. Results of similar analysis for other crops all produced ratios below 1.0. The highest observed ratio was for oats and the lowest was for soybeans. The weighted average across all the programs was just under 60 percent.

These results suggest that there is a difference between the appropriate premium rates for catastrophic coverage and buy-up policies, and that the differences are fairly large in some instances. Therefore, we believe that it is appropriate for RMA to offer a discount in the catastrophic coverage rates relative to buy-up rates. We think this is partially justified because the reduced price election that is applied to a catastrophic coverage policy is a co-payment. This suggests to us that there is a greater disincentive for moral hazard behavior on the part of producers with the catastrophic coverage policy. We also think that there is likely to be a different pool of participants purchasing CAT than the buy-up policies. ***We recommend that RMA evaluate adjusting the rates for catastrophic coverage to reflect the lower risk associated with those policies. Further we recommend that catastrophic coverage experience be treated differently than other coverage levels in the Statplan process.***

Table 6.8. Summary of 50/100 Loss Experience Relative to Catastrophic Coverage Policies

Crop	State/years	Ratio of Cat Loss Cost relative to Buy up 50% coverage Loss Cost
Wheat	599	63.8%
Oats	394	90.9%
Cotton	237	47.0%
Sugar Beets	164	33.9%
Corn	658	46.4%
Sorghum	325	55.7%
Soybeans	445	29.0%

6.11 Weighting of Experience

We considered how RMA can deal with the need to capture the effects of infrequent catastrophic weather events and give them the proper probability weights. The dilemma is that as the insurance experience time series increases in length, program changes reduce the relevance of more distant experience to the current program. We conducted sample analyses which we recommend that RMA consider as a means to improve the statistical validity of their rates by incorporating a longer series of weather experience with a relatively shorter times series of loss cost experience. While sophisticated approaches to modeling the effect of weather could be utilized, we suggest two relatively straightforward approaches to address whether experience observed in the Statplan data history reflects unusually good or poor growing conditions. The first approach considers both reweighting historical weather and accounting for acreage changes over time. Weather is addressed through a single variable, the Palmer Drought Index. We are not suggesting that this is the optimal index to use in such an exercise and recommend that additional analysis consider alternative indexes that would measure historical weather stresses. The second approach examines use of multiple weather variables to compare the weather observed in the short recent history with a longer weather data series.

6.11.1 Yield Correlation and Weighting Loss Experience Data

An issue related to the representativeness of historical weather observations is the relative weight given to historical experience. Current rating procedures used by RMA within the Statplan framework essentially assume that each year of data contributes the same amount of information to estimating expected losses. The assumption may be reasonable in cases where the underlying programs, technology, participation, and agronomic structures are relatively stable over time. However, in the case of the Federal crop insurance program, a number of factors have changed over time. In considering how to best use data collected across time, there is a need to balance concerns regarding the comparability of loss information collected over different periods with corresponding concerns relating to the relatively small samples that are available and the need to observe the effects of loss events that may be rare but large in magnitude.

A first important point to consider regarding the treatment of loss data over time involves the degree to which participation has changed. Figures 6.1 and 6.2 below illustrate participation patterns, in terms of net insured acreage, for corn and soybeans, respectively, in the three-state region that forms the heart of the U.S. Corn Belt—Illinois, Indiana, and Iowa. It is clear that participation patterns in recent years are different from those in the earlier years of the program. In particular, the 3-state total of insured corn acreage was less than 2 million acres in 1983. By 2008, this total exceeded 20 million insured acres—a 10-fold increase in participation. Similar changes are observed for other crops.

Figure 6.1. Net Corn Acreage Insured by Year in IA, IL, IN

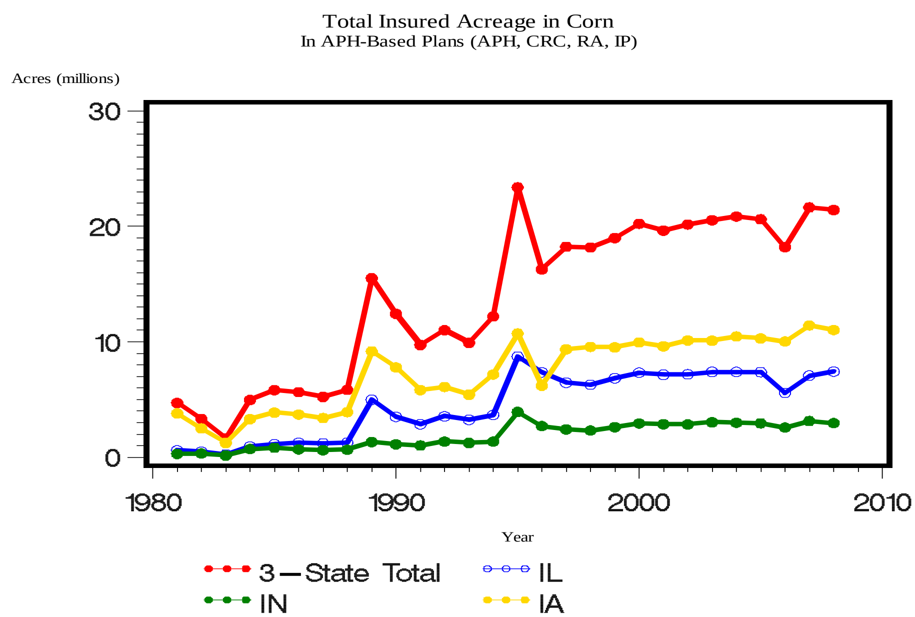
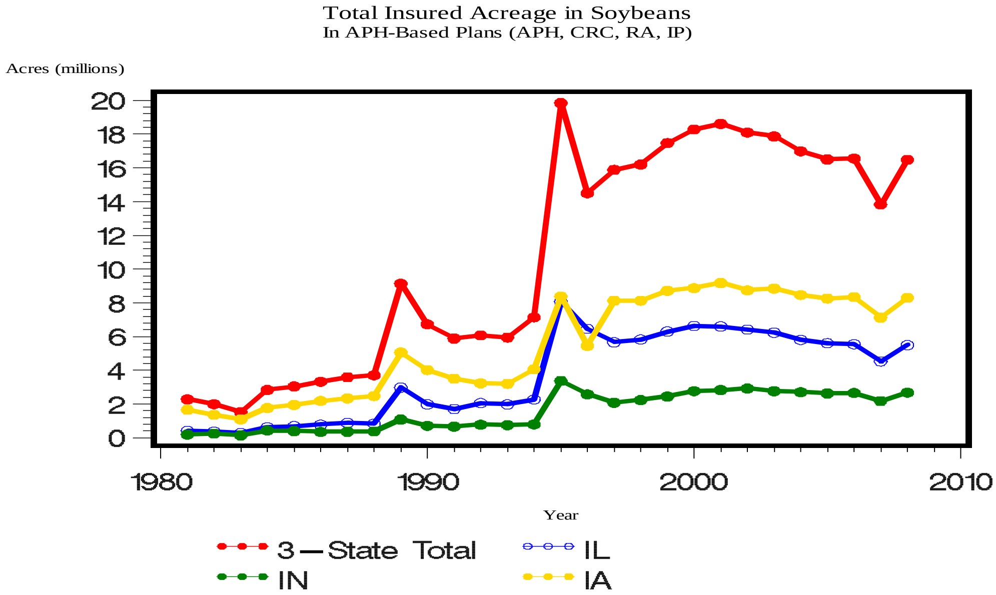


Figure 6.2. Net Soybean Acreage Insured by Year in IA, IL, IN



If all acres have similar risk characteristics or if the acres (or farmers) insured in 1981 are comparable to those insured in 2008, then the loss-experience data can be consistently compared across time, regardless of the fact that many more acres (and thus potentially more information) is available in recent years. However, the fact is that participation patterns are very different in recent years. This arises in part due to differences between current crop insurance program and the program of the early 1980s. The result of these program differences can be associated with differences in the characteristics of an insured acre in 1981 versus 2008. Program characteristics have changed, with significant increases in premium subsidies, the introduction of revenue insurance, and a number of other changes to the terms of coverage and to crop insurance offerings.

In earlier years when participation rates were low and insurance premium subsidy rates were lower, it is likely that a self-selected subset of farmers purchased insurance. In particular, it might be expected that higher risk farmers were more likely to participate in crop insurance program In addition to changes in crop insurance programs, other fundamental changes in the underlying structure of agricultural production have occurred for many crops. Perhaps most relevant are agronomic changes involving improved germplasm and biotechnological traits that have improved yield performance and reduced yield risk. These innovations have been explicitly recognized by the RMA in the recent Biotech Endorsement for corn crop insurance, which provides a premium rate adjustment for growers planting certain biotech hybrids. “Stacked” biotech hybrids, which have multiple biotech traits that improve yield performance, were introduced in the early 2000s and have been widely adopted in recent years. The most recent NASS statistics indicate that, for the U.S. as a whole, 46% of all corn planted in 2009 was of the stacked trait variety. Further, within the main Corn Belt states, stacked trait varieties accounted for 55-59% of all corn acres in 2009.[15] Other technological advancements may have also changed production risks: precision farming, seed treatments, equipment innovations, new herbicides and pesticides, and many other technological advances are constantly shaping agriculture.

The shortcomings of a relatively short span of data available for rating must be balanced against the aforementioned issues associated with changes in technology and crop insurance programs. One approach would be to estimate losses solely on the basis of more recent loss experience (say since 1997). In fact, some critics of current RMA rating methods take this approach, basing arguments about inaccurate or excessive rates on a few years of recent experience. This is equivalent to giving the recent years full weight and assigning zero weights to earlier years. Such an approach will inherently focus on a limited range of weather and loss experiences. In particular, significant systemic loss events occurred in 1988, with a widespread drought, and in 1993 with significant Midwest flooding. Any analysis that ignores such data has the potential to understate actual loss risks since data from 1997 forward tend to reflect more favorable loss experience.

One approach to incorporate these fundamental changes in the underlying structure of insurance programs and agricultural production is to choose weights for use in calculating expected or average loss costs or other measures of loss performance using data observed over time. Under the present system, RMA essentially gives each year of experience equal weight. So, if there are N years of experience, each year receives 1/N weight in calculating an average loss cost to establish rates.

An alternative is to give greater weight to recent experience. Perhaps the simplest approach would be to use some form of polynomial distributed lag model, such as Koyck or Almon lags. A simple approach is to weight data over time using declining weights of the form $w_{t-j} = \lambda^j$, where $0 < \lambda < 1$ and where w_{t-j} represents the weight assigned to observation *t-j*. Such a specification does raise questions about its ad hoc nature and the specification of appropriate values of λ.

Weighting by Acreage or Other Measures of Participation

Weights based on net acres insured would also concentrate experience in more recent years. An analogous approach would involve weighting experience by liability, once appropriate normalization of liability totals over years is undertaken to adjust for changing commodity prices or by other measures intended to capture participation changes, such as units or policies insured. A key consideration in forming weights on the basis of acreage or other measures of participation involves the extent to which the experience on individual acres (or units, policies, or dollars of liability) is independent

[15] See http://www.ers.usda.gov/Data/BiotechCrops/ExtentofAdoptionTable1.htm .

within a given year. If loss experience is perfectly correlated across acres (or other units reflecting participation), one acre provides as much information as ten thousand acres. However, as this correlation falls, the amount of information conveyed in varying levels of participation or insurance experience may differ significantly. RMA's current rating methods essentially assume perfect correlation across individual acres or units in that no adjustment is made to reflect different levels of participation across years. Again, each year out of an available sample of N years is given 1/N weight in determining the average loss-cost.

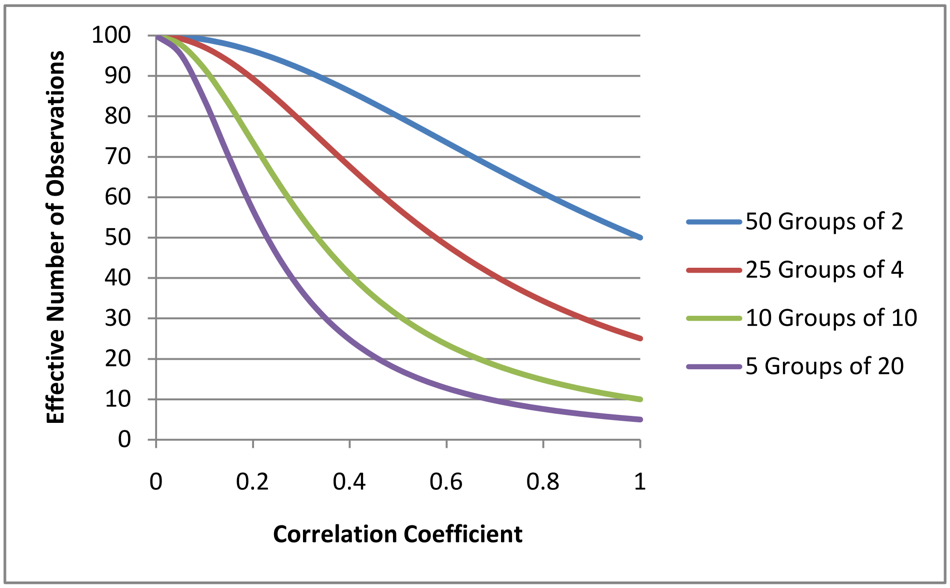
This correlation relationship plays a prominent role in the area of statistics dealing with case-control genetic association studies. In such studies, characteristics measured across multiple members taken from a common group (e.g., a family) are recognized to be non-independent. These related members are often termed "sib-pairs" (or sibling-pairs). For example, for a sample taken across N individuals, the effective number of observations may be expressed as λN, where $0 < \lambda \leq 1$. As the correlation among individuals approaches zero, λ approaches 1. However, as this degree of correlation increases, λ decreases. The effective number of observations is defined as the equivalent number of independent observations that lead to the same variance for the variable of interest.

A common measure of the number of effective observations in a correlated sample can be derived by considering the number of independent groups and then the number of individuals within the groups. For example, consider a case of 100 observations made up of 10 groups of 10. Across the groups, observations are independent. However, within the groups, observations are correlated with a Pearson (linear) correlation coefficient of ρ. The effective number of observations for this sample of 100 observations will be less than 100 if the correlation is greater than zero. In the case of *m* equally sized independent groups of sib-pairs, the effective number of observations is given by:

$$N^e = N/(1 + (m\rho -)1) \quad .$$

This concept is illustrated below in Figure 6.3 for samples of 100 observations, comprised of certain numbers of groups of correlated individuals. The first case considers 2 groups of 50 individuals, where individuals are independent across groups but correlated within groups. Likewise, the second, third, and fourth examples are comprised of 4 groups of 25, 5 groups of 20, and 10 groups of 10. Note that, as long as the correlation coefficient is zero, the effective number of observations is 100. However, as the correlation rises, the effective number of observations drops off considerably until, when observations within groups are perfectly correlated, it reaches the number of independent groups. Similar patterns are observed for the alternative samples that are comprised of differing combinations of groups. The larger the number of independent groups, the more information that is conveyed by the sample and the less the penalty for correlation within groups that is reflected in the effective number of observations.

Figure 6.3. Correlation and Effective Number of Observations



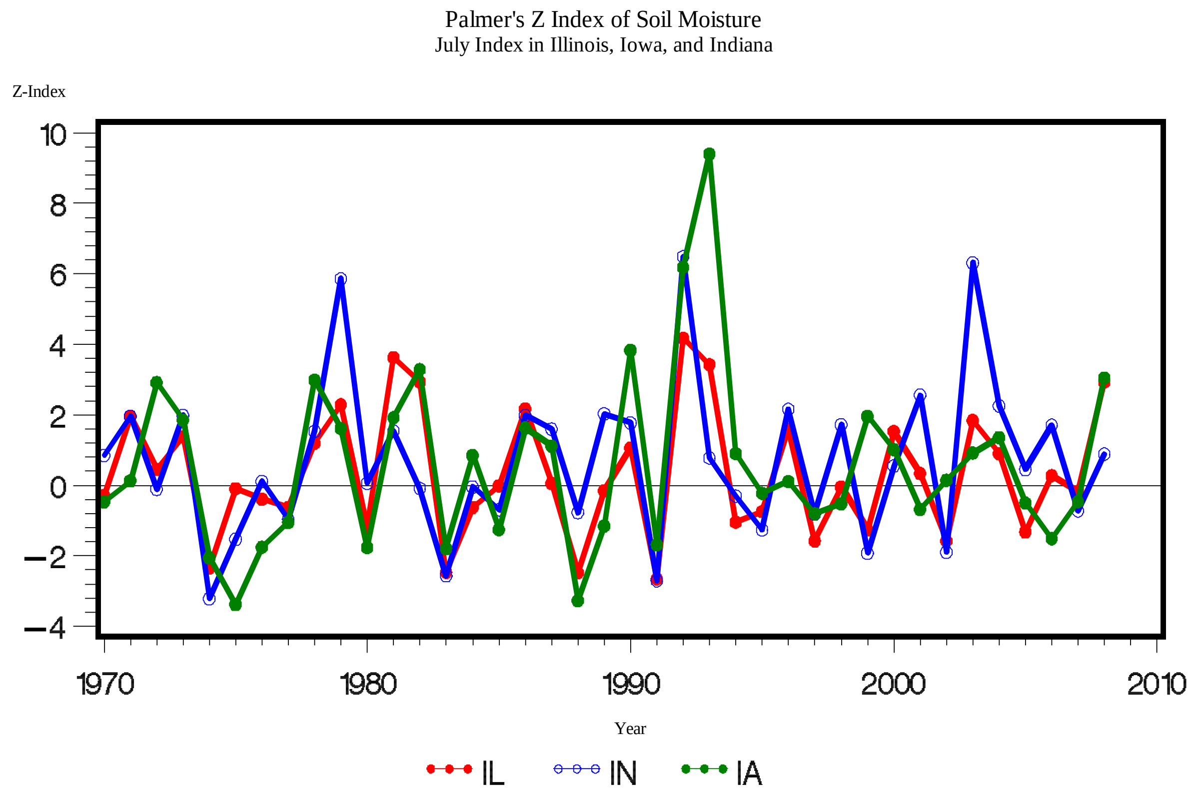
Deriving an actual correction to be made to acreage or policy counts in estimating weighted averages is much more complex than this simple example illustrates. The exact patterns of correlation and definitions of independent groups is a complex issue. It is also likely that correlation patterns vary significantly over years. A form of state-dependence where correlation tends to be stronger during extreme weather events has often been noted. Directly using acreage or policy counts to derive weighted averages of loss-costs may give too much weight to recent experience in light of the significant concentration of participation in more recent years. We believe that the issue of weighting remains an important topic for future research.

Historical Weather

Balanced against any consideration of differential weighting of experience over time is the issue of representativeness of the weather captured by a relatively short span of the RMA experience data for the longer-run typical weather. For example, 1988 and 1993 are benchmark loss years but may represent much rarer weather events than would be implied by assigning a 1/34 weighting in a simple average of 34 years of loss data. One method of adjusting experience for the representativeness of data observed over the span of observable loss experience data relative to the longer run weather experience is to use some other long-run weather index. An abundance of weather data is available. For example, the National Climate Data Center of NOAA reports a wide range of weather statistics back to 1895.

A preliminary question pertains to the degree of weather variability that has been observed in recent years. As noted, 1988 and 1993 are often considered to be benchmark years but one must consider the extent to which other years in the 1975-2008 period realized significant weather stresses that may be comparable to 1988 and 1993. Of course, any direct recognition of weather experience requires a specific index or set of indices that adequately reflect weather stresses. As an example, we consider Palmer's Z index of soil moisture. Figure 6.4 presents historical values of Palmer's Z index in July from 1970-2008. The drought of 1988 and extreme flooding of 1993 are obvious in the diagram. However, it is also apparent that weather stresses have been realized in other years as well. Perhaps most important is the fact that recent years have realized significant weather stresses in individual states. For example, Illinois realized significant drought in 1999, 2002, and 2005. Indiana also realized significant drought in 1999 and 2002. It must be acknowledged that different implications would emerge from a consideration of different indicators of weather and we are not suggesting Palmer's Z index is the best indicator of growing stresses. Further study would be required to choose the weather index or indexes that would perform best by crop and region.

Figure 6.4. July Values of Palmer's Z Index in Iowa, Illinois, and Indiana: 1970-2009

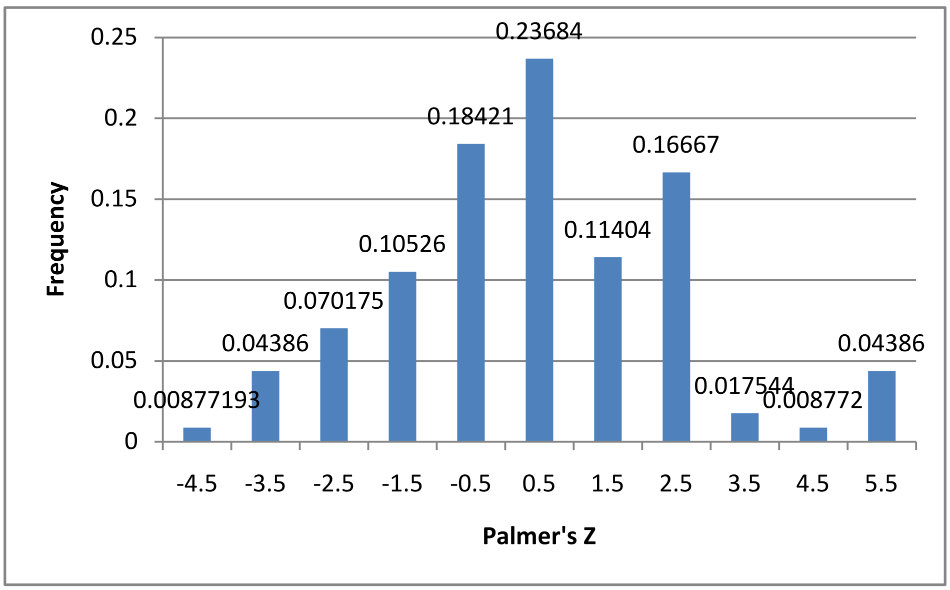


Empirical Examples of the Effects of Weighting

In order to illustrate how loss-cost experience could be weighted over time, we considered six crop/county combinations—cotton in Bolivar County, Mississippi and Scurry County, Texas; corn in Webster County, Iowa; and soybeans in Webster County, Iowa, Bolivar County, Mississippi, and Jasper County, Indiana. We considered six possible measures of the expected (average) loss cost ratio—an unweighted average, an average weighted by insured acres, an average weighted by the number of policies, an average weighted by the frequency of weather for each year in the longer history of weather, and weights constructed from the interaction of weather, acreage, and policies sold.

In order to empirically represent weather, we used the data series for the July value of Palmer's Z drought index for each state from 1895-2008. We grouped the distribution of the index into 11 discrete values (bins) and counted the frequency associated with values in each grouping over the 1895-2008 period. An example of the resulting distribution is presented in Figure 6.5.

Figure 6.5. Frequency Distribution of July Value of Palmer's Z Index in Indiana (1895-2008)



Weighted average loss-costs from the six alternative weighting methods are presented in Table 6.9 below. It is important to again emphasize that this empirical exercise is meant merely to illustrate how alternative weighting schemes might be applied and how the resulting loss-cost estimates may be affected. The average loss-costs illustrate that the estimates may be sensitive to the specific weighting scheme employed. In most cases, the estimates obtained by weighting by a weather index are closest to the unweighted averages, which may suggest that the current unweighted approach to rating may provide a reasonably accurate representation of long-run weather patterns, at least as such is reflected in our particular choice of index. In most cases, weighting by acreage or policy counts tends to produce lower rates. In short, there is little available information to recommend one weighting scheme over another and we believe that this should remain a topic for future research and evaluation. As it stands, the current weighting methodology appears to produce estimates reasonably consistent with those emerging from an evaluation of historical weather patterns.

6.11.2 Adjusting for Unrepresentative Weather in Short Loss Experience Data

We also investigated an alternative approach to account for historical weather. This section briefly describes this alternative approach. The analysis conducted is structured as follows. We assumed that RMA takes the annualized summary Statplan data for a particular county that has had the standard adjustments made to put loss experiences on a comparable basis. This results in a single observation for each historical year of loss cost experience for a county/crop program. For our illustration we use Statplan data from 1985 forward to illustrate a scenario where RMA wished to omit older experience. The weather data is then matched with weather data from a nearby weather station. In our analysis, we used data from the United States Historical Climatology Network (USHCN) web site, which gives historical data for weather locations in the contiguous United States. This data source has 1,218 observation stations from the 48 contiguous states. These weather stations are chosen to be dispersed across the United States, but also tend to be located in less urbanized areas for consistency and a lack of human urbanization effects near the weather station. For many of the locations, data are available back to 1895. Thus one has over 100 years of available weather experience.

In our analysis we use monthly average precipitation and mean temperature data for the growing season of the crop analyzed. These data are merged by year with the Statplan data set available from RMA. This is an admittedly simplistic set of weather variables for explaining variation in the observed loss cost ratios. The monthly variables used are an average temperature and rainfall for two-month periods beginning in May through the primary growing season. So, the average temperature for the May/June period and the July/August period are computed along with squared terms and interaction terms between temperature and rainfall within the two-month period. So, econometrically a model is specified with the loss cost ratio dependent variable regressed on a linear and squared term for May/June temperature, July/August temperature, May/June precipitation, July/August precipitation, and a May/June interaction between rainfall and temperature and a July/August interaction between rainfall and temperature. This is our base model, although in some locations we omit variables due to a lack of statistical significance of some of the terms. We proceed by estimating a predictive model of loss cost using the time period over which the weather data and Statplan data overlap. In many instances between 70 and 80 years of additional weather data extend beyond the time series of the Statplan data base.

Table 6.9. Alternative Weighted Measures of Loss-Ratios and Loss-Costs

Crop	FIPS	Weighting Factor	Loss Ratio	Loss-Cost from SOB	Loss-Cost from Statplan
21	28011	Unweighted	0.8763	0.0709	0.0814
21	28011	Acres	0.8180	0.0709	0.0559
21	28011	Policies	0.8288	0.0697	0.0545
21	28011	Weather Frequency	0.8230	0.0675	0.0833
21	28011	Weather Frequency*Acres	0.7878	0.0712	0.0553
21	28011	Weather Frequency*Policies	0.7845	0.0680	0.0525
21	48415	Unweighted	1.6604	0.3003	0.2867
21	48415	Acres	1.6951	0.3299	0.3142
21	48415	Policies	1.8006	0.3319	0.3171
21	48415	Weather Frequency	1.8311	0.3165	0.2986
21	48415	Weather Frequency*Acres	1.8541	0.3451	0.3242
21	48415	Weather Frequency*Policies	1.9742	0.3509	0.3320
41	19187	Unweighted	0.5026	0.0183	0.0163
41	19187	Acres	0.4356	0.0178	0.0107
41	19187	Policies	0.4507	0.0173	0.0118
41	19187	Weather Frequency	0.3502	0.0129	0.0139
41	19187	Weather Frequency*Acres	0.2984	0.0122	0.0074
41	19187	Weather Frequency*Policies	0.3132	0.0122	0.0081
81	18073	Unweighted	0.9361	0.0366	0.0254
81	18073	Acres	0.6244	0.0321	0.0220
81	18073	Policies	0.6502	0.0315	0.0222
81	18073	Weather Frequency	0.8831	0.0314	0.0222
81	18073	Weather Frequency*Acres	0.4904	0.0221	0.0146
81	18073	Weather Frequency*Policies	0.5266	0.0223	0.0155
81	19187	Unweighted	0.6671	0.0238	0.0159
81	19187	Acres	0.5868	0.0230	0.0162
81	19187	Policies	0.5947	0.0225	0.0164
81	19187	Weather Frequency	0.4658	0.0172	0.0118
81	19187	Weather Frequency*Acres	0.4049	0.0166	0.0116
81	19187	Weather Frequency*Policies	0.4028	0.0159	0.0114
81	28011	Unweighted	1.4083	0.1563	0.1163
81	28011	Acres	1.1260	0.1192	0.0913
81	28011	Policies	1.2710	0.1383	0.1035
81	28011	Weather Frequency	1.4334	0.1569	0.1248
81	28011	Weather Frequency*Acres	1.1468	0.1188	0.0918
81	28011	Weather Frequency*Policies	1.2833	0.1367	0.1046

-

We estimate a Tobit model of loss cost because the loss cost ratio variable is censored at zero. This prevents our predictive model from predicting a loss cost below zero.

The structure of the Tobit model is:

$$y_i^* = x_i\beta + \varepsilon_i$$

where $\varepsilon_i \sim N(o, \sigma^2)$. The observed y is defined by the following measurement equation

$$y_i = \begin{Bmatrix} y^* if\ y^* > 0 \\ 0\ if\ y^* \leq 0 \end{Bmatrix}$$

Importantly the expected loss cost is written as:

$$E[LC] = \Phi(\frac{x_i\beta}{\sigma})[x_i\beta + \sigma\lambda]$$

where λ is the inverse mills ratio

Once the loss cost predictive model is estimated, we calculate the average loss cost observed during the time period when loss cost data were available, and the predicted values of the tobit loss cost model given the weather data observed for the full time series back to 1895. This allows us to predict what the loss cost would have been given weather that occurred in a time period prior to the crop insurance program's observed data. Thus, we are able to backcast loss cost ratios. We then take the mean predicted loss cost ratio over the full 108-year period between 1895 and 2008 and compare it to the predicted loss cost ratio in recent periods to derive a ratio of recent loss cost to the longer period. Table 6.10 shows an example of the estimated model for Fort Dodge county, Iowa soybeans. The 24 observations are used to estimate the relationship of the various weather variables and the observed loss cost.

Our interpretation of this comparison is to see whether the predicted loss cost ratios for the most recent period where RMA has available data, is greater or less than for the longer time period. For example, if the average predicted loss cost ratio in the most recent period for a particular location is five percent and the average loss cost over the 108-year period is six percent, this would suggest that the most recent time period has experienced weather that is more favorable than over the longer period. Conversely, if the average predicted loss cost ratio over the full time period is less than that observed in the actual experiences of the program, this would suggest that insurance program has experienced worse weather events in the recent observed period than over the longer time span.

Table 6.10. Fort Dodge County Iowa Loss Cost Model

Number of Observations	**24**						
Name of Distribution	**Normal**						
Log Likelihood	**61.03659237**						
Analysis of Parameter Estimates							
Parameter	DF	Estimate	Standard Error	95% confidence Limits		Chi-Square	PR>Chi sq
Intercept	1	-2.3014	0.4957	-3.2729	-1.3299	21.56	<.0001
May/June Temp	1	0.018	0.0046	0.0091	0.027	15.54	<.0001
July/Aug Temp	1	0.016	0.006	0.0042	0.0278	7.07	0.0079
May/June Interaction	1	-0.0035	0.0011	-0.0056	-0.0014	10.73	0.0011
July/Aug Temp	1	-0.0031	0.0012	-0.0054	-0.0007	6.25	0.0124
May/June Precip	1	0.232	0.0698	0.0953	0.3687	11.06	0.0009
July/Aug Precip	1	0.2055	0.089	0.0309	0.38	5.32	0.021
July/Aug Precip Square	1	0.0018	0.0009	0	0.0037	3.84	0.0502
Scale	1	0.019	0.0027	0.0143	0.0252		

Our seven example county/crop programs are shown in Table 6.11. The predicted value over the actuarial period is reported first, then for the longer period and then the ratio of the two is reported in the final column. Note that in some cases the ratio is above 1.0 and in others below 1.0, suggesting differences between the actuarial period and the longer weather period. For example, in Bolivar County soybeans the ratio of less than 0.97 suggests recent experience is the result of better than average weather. Conversely, Fort Dodge county Iowa corn and soybean appear to have incurred actuarial experience about 14% worse than one would expect over the longer period.

Table 6.11. Comparison of Actuarial Period to Long-term Predicted Loss Cost

Location and Crop			Actuarial Period Mean Predicted Loss Cost	1895-2008 Period Mean Predicted Loss Cost	Ratio actuarial Period/Longer Period
Audrian Co	Mo	Corn	0.089	0.090	0.984
Bolivar Co	MS	Cotton	0.061	0.060	1.014
Bolivar Co	MS	Soybeans	0.095	0.098	0.967
Fort Dodge Co	IA	Soybeans	0.024	0.021	1.147
Fort Dodge Co	IA	Corn	0.020	0.017	1.146
Scurry Co	TX	Cotton	0.284	0.282	1.005
Jasper Co	IN	Soybeans	0.038	0.042	0.911

Conclusions and Recommendations

We have reviewed the implications of changes in the crop insurance program as well as structural changes in the agronomic setting underlying recent experience for current rating procedures. At present, these procedures assign equal weight to each year's experience in calculating an expected (average) loss cost ratio. We point out that crop insurance participation patterns have changed significantly over time, with current participation being ten-fold larger in terms of acreage insured or total liability than was the case in the 1980s. We also discuss the implications of technological innovations that may have altered yield performance and risk over time. These innovations include significant advances in biotechnology. RMA has made explicit adjustments for these innovations in its Biotech Endorsement (BE).

We note the approach taken here makes several assumptions that RMA should recognize. First, as specified in our examples, climate change is not addressed. We have assumed all years of weather data are equally likely. A second caveat to our preliminary analysis is that weather variables do not fully explain loss cost experience and functional form is uncertain. We also anticipate that in some crops/regions the model fit will be relatively poor. It may be that estimating these relationships at a more aggregate level (e.g. state/crop) would be preferred.

We recommend that RMA evaluate alternative loss cost experience weighting methods. Our analysis suggests it is feasible to incorporate additional weather information into the rating system and to allow additional weight be placed on more credible annual observations. However, we do not offer specific recommendations for changing the manner in which experience is weighted over time in current rating methods. We believe a detailed study of this issue should investigate both optimal weights and implementation issues.

6.12 Using a Loss Ratio Approach Rather than Pure Premiums

The current pure premium approach to developing a base rate requires that the data be massaged extensively to restate all experience on a common basis. When there were fewer choices in the program, this was a much easier exercise, although it has always included some rather ad hoc adjustments that were not necessarily actuarially sound, such as the interpolation adjustment to approximate unobserved experience for producers electing lower than 65% coverage. This adjustment made very little difference to the end result when the proportion of producers below 65% coverage was low, but as more and more producers opt into the program, the proportion of producers with coverages both above and below 65% coverage has increased, making the adjustment more and more important. This is just one example where the data adjustment is ad hoc. There are other cases where no adjustment is made at all, such as for the distribution by type/practice discussed in section 6.3.

One way to avoid the need for such adjustments in the development of the base rate would be to adopt a loss ratio rather than pure premium approach. The following is an outline of how that might be done. A more extensive study, with testing on several data sets, would be needed before we could make a strong recommendation, but we believe that this approach is at least worth exploring in further detail.

Consider the fact that the current base rate represents in a single value the entire time series of experience to date. It also provides a starting point from which all producer premiums are determined. If the base rate in use is equal to the indicated rate, then the expectation is that the experience over the long run using that base rate will produce a loss ratio of 100%. Let Bi be the base rate in year *i*. How is B_1 related to B_0? The current ratemaking methodology would suggest that they are unrelated, but in fact B_1 is merely the result of adding one more year to the time series that produced B_0. This suggests that B_1 can be calculated without resorting to restating the entire history. If B_0 is based on N years of experience and expected to produce a loss ratio of 100% and the loss ratio for year 0 is *X*%, then the expected loss ratio for year 1, given B_0 and the loss ratio for year 0, is $Z = \frac{N \times 100\% + 1 \times X\%}{N+1}$ and $B_1 = Z \times B_0$.

If the current base rate is not equal to the indicated rate due to capping, then the a priori expected loss ratio, rather than 100%, is the ratio of the actual rate to the indicated rate: $\frac{B_0}{B_i}$. The a posteriori expected loss ratio is $Z = \frac{N \times \frac{B_0}{B_i} + 1 \times X\%}{N+1}$, and the indicated rate for year 1 is $B_{i+1} = Z \times B_0$.

Where the data are thin, the indicated base rate based on county-only experience gets credibility weighted with the circle experience. The credibility-weighted indicated rate is a "better" estimate of the expected 100% ratio rate than the rate based on county experience alone. Clearly, the credibility weighting methodology would need to be adjusted to determine how much weight to give to the new year's experience for both the county and the circle, but the objective remains to determine how much the addition of another year's experience adjusts the base rate.

A loss ratio approach study would also need to address how to manage the catastrophe procedure. We note, however, that Milliman (2008) has considered a loss ratio approach rather than a pure premium approach to identifying how much of county experience should be spread to the state. It would also be easier to work with if the CAT load were multiplicative rather than additive in cases where there is a long time series of data indicating that the cat exposure is not uniform across a state.

Rating Factor Adjustments

All of the above has no effect on adjustments to any of the rating factors. The proper factor for type or practice still has to be calculated separately from the base rate, just as it is today. However, once prior experience has been adjusted once for type/practice mix changes as discussed in Section 6.3, moving to a loss ratio methodology removes the need to readjust the prior experience. Once an actuarially sound base rate for an identified base type/practice has been established, the overall rate level is adjusted by increasing or decreasing that base rate, while the relationships among types/practices are adjusted by changing the type/practice relativities. Changing a type/practice relativity, however, also has an effect on the overall rate level, properly accounted for by an offsetting change in the base rate. For example, if there is an *X*% discount given for a particular type or practice and a rating study indicates that the discount should be *Y*%, then the effect on the indicated base rate is as follows:

B_0 = indicated 100% loss ratio base rate with discount at *X*%

p = proportion of insureds with discount

All other things being equal, the premium with a discount of *X*% will be $B_0 \times (1-p) + B_0 \times (1-X\%) \times p$. The total premium needs to be unchanged, so the adjusted base rate B_{0*} will need to be **Error! Bookmark not defined.** $B_0 \times \frac{1-X\%p}{1-Y\%p}$.

This is called an off balance adjustment. The calculation of the off balance is a bit more complicated where the rating factor is additive rather than multiplicative, but is easier than the requisite reweighting of the experience discussed in section 6.3 to maintain a balanced loss cost.

We note that virtually all property/casualty rates are made using a loss ratio approach that applies an indicated change based on recent experience to an existing rate structure. Loss ratio methods are employed in most cases because they remove most of the need to adjust prior experience for changes in distribution by classification. As the number of "classes" (types/practices/options) permitted by RMA increases, the loss cost method of setting rates becomes either considerably more cumbersome or less and less accurate. ***We recommend that RMA undertake a comprehensive study of the loss ratio method for determining future rate changes, perhaps in conjunction with a study aimed at a State level top-down approach as recommended by Milliman*** (2008).

7.0 Evaluation of Procedures to Develop COMBO Revenue Rates

7.1. Introduction and Overview

The combo policy will integrate existing APH-based crop insurance plans into a common umbrella crop insurance policy that has a number of options for yield and revenue coverage. This allows the common and basic provisions of the underlying crop insurance plans to be the same across different coverage options. The combo policy represents a straightforward extension of the design and methods underlying the Revenue Assurance (RA) policy, albeit with some important modifications that more closely resemble the current rating methods used for Crop Revenue Coverage (CRC). These modifications arise because the method involves summation of several independent components in a manner analogous to the piece-wise design of the CRC policy.

The development of the combo policy was preceded by two contracted studies that evaluated rating methods relevant to yield and revenue insurance plans. One study addressed the issue of rate relativities and recommended a change to RMA's long-standing practice of using fixed rate relativities for all crops and counties. RMA adopted this study's recommendations and now bases rates at coverage levels different from 65% on variable rate relativities that depend on the underlying rates and other characteristics of the county's experience. The motivation for this study and its conclusions reflected concerns over rate differences for what was essentially identical coverage under the RA-HPO and CRC plans. A second study undertaken by AgRisk Management, LLC recommended that RMA adopt the rating methods used in establishing RA and RA-HPO premium rates—a recommendation that RMA has partly accepted in rating the combo plans.

7.1.2. Brief Description of the Combo Rating Method[16]

The combo rating method is adapted from various components of the RA and CRC rating approaches. The combo rating procedure follows from the RA rating in the sense that rates are derived from a parametric yield distribution. The parameters of the yield distribution are essentially calculated by calibrating a specific parametric probability density function (PDF), a censored normal in this case (see discussion below), so that it corresponds to a distribution having a mean equal to the farmer's underlying APH yield and a rate that is equal to the underlying APH rate at the 65% coverage level. The important underlying assumption in this approach is that the APH yield rates are correct. This assumption is consistent with the CRC rating approach. Combo rating also follows the RA method in assuming that the price distribution is assumed to follow a lognormal distribution and its parameters can be computed based on an options based volatility

[16] The brief description of the combo rating procedure in this section is based primarily on the RMA document "RMA Revenue Rating An Analysis of the Combo Rating Method."

measure. The parameters of the yield and price distributions, together with an assumed degree of yield-price correlation, are then used in a simulation procedure to calculate a revenue rate at various coverage levels. Consistent with the CRC rating approach, a "revenue load" is then calculated by taking the difference between the simulated revenue rate and a corresponding simulated yield rate (for yield insurance coverage). This revenue load is then added to the empirical APH yield rate to get the premium rate that will eventually be charged to an insured choosing revenue coverage under the combo policy.

The combo rating process can be basically divided into four components: (1) Calculating price and yield correlations, (2) Calculating the mean and standard deviations (i.e. the parameters) of the yield and price distributions, (3) Deriving the correlated yield and price draws, and (4) Simulating losses and calculating revenue/yield rates. These components are succinctly described below.

The yield-price correlations used in combo rating are calculated from yield and price deviates from 1990 to 2005. The National Agriculture Statistics Service (NASS) county yield data are detrended using a linear tend and the yield deviates are calculated as the percentage deviation from trend. The price deviates, on the other hand, are calculated as the percent change in price from the expected price to the harvest price. Once the price and yield deviates have been calculated, the county-level yield-price correlations are derived and then state-level yield-price correlations are computed by taking the weighted average of the county-level correlations (i.e. weighted by production). The state-level correlations are then adjusted downward to more accurately reflect the yield-price correlation at the individual level. A 1990 to 2005 period was chosen to calculate the county-level correlations because it can be argued that significant changes in agricultural policy have occurred prior to this period (i.e. from the 1985 Farm Bill) that could have caused structural changes in the relationship between yield and prices. Choosing the 1990 to 2005 period avoids this structural break. One limitation of the procedure used to calculate the yield-price correlations is that it imposes a constant yield-price correlation for all producers in the state.

As mentioned above, the parameters of the price distribution (i.e. mean and standard deviation) are calculated primarily using an options based volatility measure and assuming that prices are log-normally distributed. The assumption of log-normality is consistent with the Black-Scholes option pricing method that is commonly used by traders. On the other hand, the yield distribution in the combo rating method is assumed to follow a censored normal distribution. This is in contrast to the beta distribution used in the RA rating approach.[17] The procedure to derive the parameters (i.e. the mean and standard deviation) of the censored normal yield distribution corresponding to the APH yield insurance rate at the 65% coverage level is as follows:

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[17] As will discussed later in this chapter, the main argument for using the censored normal instead of the beta is the perceived practical/computational difficulty in working with distribution due to the lack of a closed form solution. Note that we do not necessarily agree with this argument (See Minor Comment (4) in section 8.3 below). The AgRisk Management, LLC report also justified the use of the censored normal by showing that the rates derived from a censored normal and a beta are fairly similar.

(1) Normalize the APH yield to a value of 100 (i.e. μ=100),
(2) Select a target APH rate (i.e. the target rate)
(3) Find μ and σ that ensure that the following two equations hold:

(Eq. 7.1) $$100 = \frac{1}{5000}\sum_{i=1}^{5000}\max(y_i, 0)$$

(Eq. 7.2) $$\text{Target Rate} = \frac{\frac{1}{5000}\sum_{i=1}^{5000}\max(0, 65-\max(y_i, 0))}{65},$$

where $y_i = z_i \cdot \sigma + \mu$ and z_i is the standard normal deviate.

(4) Transform the parameters in step (3) for APH yields other than 100 by using the following formulas:

(Eq. 7.3) $$\tilde{\mu}_y = \frac{APH \times \mu}{100}$$

(Eq. 7.4) $$\tilde{\sigma}_y = \frac{\sigma}{\mu} \times \tilde{\mu}_y .$$

Once these yield and price parameters are calculated, the correlated yield and price draws can then be determined. First, 500 draws are calculated from the inverse normal of Babcock's Nearly Uniform Sequence. This is a low discrepancy sequence (a variant of the rectangular rule also called quasi-random sequences) that ensures that even with a lower number of draws, on average, these draws can still be consistent with a uniform distribution. In general, such quasi-random numbers converge faster than pseudo-random numbers and the results from quasi-random numbers tend to be more accurate than with pseudo-random numbers using the same number of points/draws (See Morokoff and Caflisch, 1994). Due to the relative accuracy of the quasi-random sequence, the number of draws can be reduced to improve computational speed. After the 500 draws are determined, the Iman and Conover (1982) method is used to impose the state-level yield-price correlations calculated in step (1) of the combo rating process. This method allows arbitrary marginal distributions (the censored normal yield distribution and the log-normal price distribution in this case) to be combined into a joint distribution with a specified correlation. The Iman and Conover (1982) method is a computationally simple algorithm of imposing correlation that has already been used in rating an existing crop insurance product (the Livestock Gross Margin (LGM) product).

Using the deterministic points from the 500 correlated draws, yield and revenue rates (e.g., the Harvest Price Revenue Rate (HP Rate) and the Harvest Price Exclusion Option

Revenue Rate (HPEO Rate)) can then be calculated using the following formulas (i.e. this process is also called a quasi-Monte Carlo simulation):

(Eq. 7.5) $$\text{Yield Rate} = \sum_{i=1}^{500} \frac{\max(0, C \cdot Y - \max(0, y_i \cdot \tilde{\sigma}_y + \tilde{\mu}_y))}{500 \cdot Y \cdot C}$$

(Eq. 7.6) HP Rate =
$$\sum_{i=1}^{500} \frac{\max(0, C \cdot Y \cdot \min(2 \cdot P, \max(P, \tilde{p})) - \max(0, (y_i \cdot \tilde{\sigma}_y + \tilde{\mu}_y) \cdot \min(2 \cdot P, \tilde{p})))}{500 \cdot Y \cdot C \cdot P}$$

(Eq. 7.7) $$\text{HPEO Rate} = \sum_{i=1}^{500} \frac{\max(0, C \cdot Y \cdot P - \max(0, (y_i \cdot \tilde{\sigma}_y + \tilde{\mu}_y) \cdot \min(2 \cdot P, \tilde{p})))}{500 \cdot Y \cdot C \cdot P}$$

where C is the coverage level, Y is the APH yield, P is the planting time price, y_i is the yield draw, and $\tilde{p}$ is the log-normally distributed harvest time price draw (calculated based on the parameters of the lognormal price distribution as follows: $\tilde{p} = e^{\sigma_p \cdot p_i + \mu_p}$).

The “revenue load” can then be calculated as follows:

HP Combo Revenue Load = HP Rate – Yield Rate
HPEO Combo Revenue Load = HPEO Rate – Yield Rate.

The resulting combo premium rates are then derived using the following formulas:

HP Combo Premium Rate = APH Base Premium Rate + HP Combo Revenue Load
HPEO Combo Premium Rate = APH Base Premium Rate + HPEO Combo Revenue Load.

Given the rate calculations above, it is important to emphasize that the actual combo revenue rate is not the simulated revenue rate per se, but instead it is the APH Base Premium rate added to the difference between the simulated revenue rate and simulated yield rate. This captures the additional price risk from insuring revenue and ensures that even as yield risk approaches zero there will still be a positive premium to account for price risk. In addition, this “revenue load” approach is consistent with the CRC rating methods.

7.1.3. Outline of the Combo Review Section

Our review of the combo rating methods below identifies issues that we believe merit additional consideration. None of these issues is considered to be so serious as to inhibit the implementation of the combo plan. However, we do believe that these issues merit additional consideration as the combo plan is implemented, since the revenue options available under the combo plan will likely account for the largest share of liability and premium in the program. Moreover, it should be noted that in this review of the combo policy and its associated rating methods, we specifically reviewed two documents. The first is the aforementioned internal RMA document entitled “RMA Revenue Rating: An Analysis of the Combo Rating Method” (See footnote 17). A second document, which appears to have preceded the RMA documentation of the combo rating, is an unpublished contract study entitled “Development of a New Rating Method for Multi-Peril Crop Insurance”

Our review in this chapter proceeds according to the following plan. We first focus on what we believe to be the most significant issue associated with the design and rating of the combo plan—an inconsistency in treatment of rate relativities. It is important to note that the combo rating methods initially reject RMA’s current empirical rate relativities (from the current APH yield insurance rating approach) and instead impose the relativities associated with the parametric distribution assumed to govern the crop yields. This difference is later “reconciled” by adding the implied “revenue load” that is given by the difference between the combo revenue rate (derived from the combo rating methods) and the combo yield rate to the associated APH yield rate, which therefore embeds RMA’s current relativities. We identify important shortcomings that may be associated with this rating approach. Most important is that this approach involves an inconsistency in that two different yield distributions are implied—one based on the calibrated censored (discrete/continuous) normal distribution and another based upon the current rate relativities. As we show below, these distributions may differ substantially. In the next section of the review, we then identify a number of minor issues that RMA may wish to consider. None of these issues is considered to be critical.

7.2. Combo Rate Relativities

As we have noted, the combo rating approach incorporates a design element that may result in inaccurate or at least inconsistent rates across different insurance options. One distribution is used to model yield rates, revenue rates, and a revenue loading factor that is given by the difference in revenue and yield rates. This loading factor is then added to the APH yield rates at coverage levels away from 65% to obtain the final revenue rates. This essentially involves the use of one distribution and set of relativities to obtain the revenue load and another distribution and set of relativities to establish the revenue rate. Regardless of the extent to which the resulting revenue rates differ in practice, this procedure does involve an inconsistent approach to rating.

Several alternatives that could eliminate this inconsistency are apparent. The first and perhaps preferred method is to calibrate the parametric yield distribution across the *entire range* of rate relativities rather than at a single rate, when calculating the revenue load. Of course, it may not be possible to perfectly replicate the entire distribution across all coverage levels but it is generally possible to achieve a very accurate calibration to the entire range of rates, provided an appropriate parametric distribution is used in the calibration. As we demonstrate below, it is possible to calibrate a four-parameter beta distribution that has two free parameters to the existing RMA relativities to a high degree of accuracy in many cases. On this point, note that such a beta distribution may offer considerably more flexibility than the two-parameter beta that has been used in rating the RA plan. In the RA case, rather rigid assumptions are used to assign a minimum and maximum yield, which severely constrains the flexibility of the resulting distribution. In contrast, allowing these parameters to fit the entire span of rates across different coverage levels provides a more accurate and flexible approach. Alternatives to the use of a beta distribution include the recommended censored normal density and other parametric specifications, including the Weibull and mixtures of normals.

A second natural approach would be for RMA to completely abandon the empirical rate relativities currently in use and instead use the relativities associated with the calibrated combo censored normal distribution. We do not recommend this approach in that the current rate relativities have been chosen on the basis of an empirical analysis of loss experience—an approach that we believe is likely to be superior to any assumed parametric distribution.

As it stands, we believe consistency in rating dictates that a single distribution and set of relativities should be used in rating the yield and revenue components of the combo plan. This would involve a choice of either using the current empirical relativities or adopting the relativities implied by a censored normal distribution in both rating the APH yield plans and the revenue plans.

A relevant question involves the extent to which this inconsistency results in important differences in rates and revenue loads. In order to provide some empirical evidence on this issue, we considered an evaluation of the 2009 APH premium rates for selected major growing regions for four important crops. We considered rates for all practices on corn and soybeans in all counties in Iowa, Illinois, and Indiana. We considered cotton rates in Georgia, Mississippi, and Texas. Finally, we considered wheat rates in Nebraska and Kansas.

Absolute percentage differences between current relativities and the relativities inherent in the combo rating methodology are presented in Table 7.1. Because the combo rating method calibrates to the 65% rate, the difference should be zero at the 65% coverage level. Any modest differences reflect approximation errors in the optimization routine used to calibrate the censored normal distribution to the rate and APH yield.[18] In general, the relative (proportional) differences in premium rate relativities tend to be highest at the 85% coverage level. The absolute proportional differences suggest average rate relativity differences of 13%, 17%, 19%, and 8% for corn, soybeans, cotton, and wheat, respectively. As expected, differences also increase at lower coverage levels as one

[18] Note that we used a simple nonlinear optimization algorithm to calibrate the density to the 65% rate and the APH yield. This calibration routine may offer advantages in implementing the combo plan in that no simulation or random draws are needed.

moves away from the 65% coverage level. Differences at the 50% coverage level tend to range from 6-18%.

We selected several crop and practice combinations to illustrate differences in the rate relativities across the range of coverage levels. Examples of these differences are plotted in Figures 7.1 and 7.2. Of course, both relativities are defined to be 1.0 at the 65% coverage level. The patterns demonstrated in Table 7.1 are reinforced in the diagrams.

For most of the counties examined, the combo rate relativities are typically steeper, implying relativities that are higher than those currently in use at coverage levels above 65% and lower than current relativities for coverage levels less than 65%. However, this is not always the case (as seen in Figures 7.1 and 7.2). In some cases, rather extreme differences in relativities are apparent. These cases tend to occur when the combo relativities are much flatter than those implied by the empirical relativities, implying lower rates at higher coverage levels. Figures 7.3 and 7.4 present a summary of the geographic differences in the differences in relativities.

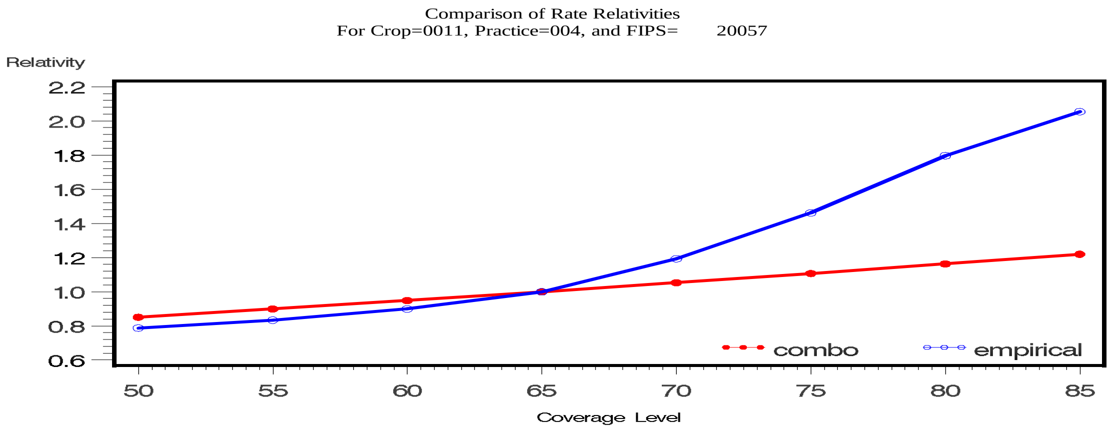
Table 7.1. Summary of Evaluation of Absolute Percentage Differences between Current RMA Empirical Yield Rate Relativities and Proposed Combo Rate Relativities

Coverage Level	Mean	Std	Min	Max
Wheat				
50	0.0631	0.0236	0.0019	0.1508
55	0.0492	0.0184	0.0011	0.1171
60	0.0281	0.0104	0.0004	0.0647
65	0.0000	0.0000	0.0000	0.0000
70	0.0263	0.0150	0.0004	0.1283
75	0.0469	0.0291	0.0002	0.2427
80	0.0638	0.0423	0.0006	0.3527
85	0.0790	0.0550	0.0001	0.4063
Cotton				
50	0.0947	0.0690	0.0001	0.3054
55	0.0636	0.0497	0.0003	0.2093
60	0.0296	0.0244	0.0002	0.1072
65	0.0001	0.0009	0.0000	0.0226
70	0.0553	0.0328	0.0003	0.1577
75	0.1030	0.0568	0.0001	0.2960
80	0.1460	0.0736	0.0011	0.4199
85	0.1897	0.0883	0.0033	0.5102
Corn				
50	0.1754	0.0642	0.0727	0.4194
55	0.1236	0.0441	0.0443	0.2831
60	0.0662	0.0258	0.0238	0.1361
65	0.0000	0.0000	0.0000	0.0000
70	0.0289	0.0217	0.0004	0.1005
75	0.0608	0.0453	0.0000	0.2096
80	0.0940	0.0693	0.0003	0.3233
85	0.1266	0.0929	0.0008	0.4370
Soybeans				
50	0.1422	0.0702	0.0009	0.3423
55	0.0685	0.0499	0.0008	0.1915
60	0.0306	0.0244	0.0000	0.0919
65	0.0000	0.0000	0.0000	0.0000
70	0.0440	0.0294	0.0001	0.0977
75	0.0891	0.0601	0.0003	0.1917
80	0.1321	0.0898	0.0004	0.2830
85	0.1720	0.1173	0.0003	0.3687

Note: Absolute percentage difference defined as |(Current-Combo)/Current|.

Figure 7.1. Examples of Differences in between Current RMA Empirical Yield Rate Relativities and Proposed Combo Rate Relativities

A. Wheat



B. Cotton

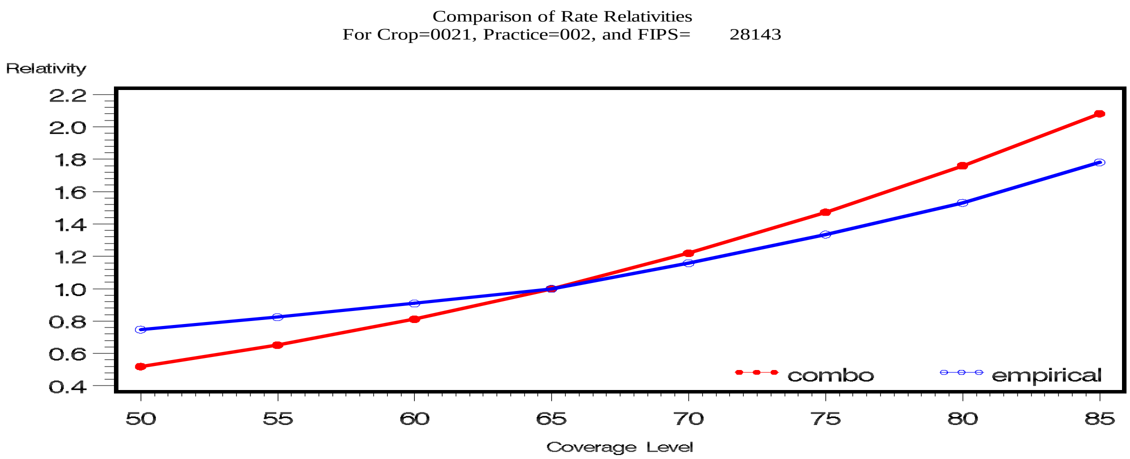
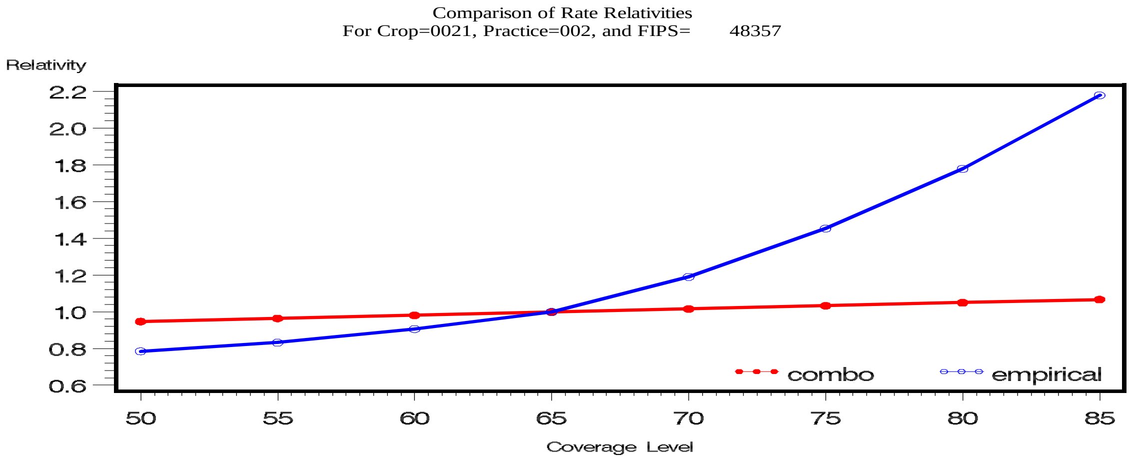


Figure 7.2. Examples of Differences in between Current RMA Empirical Yield Rate Relativities and Proposed Combo Rate Relativities

A. Cotton



B. Corn

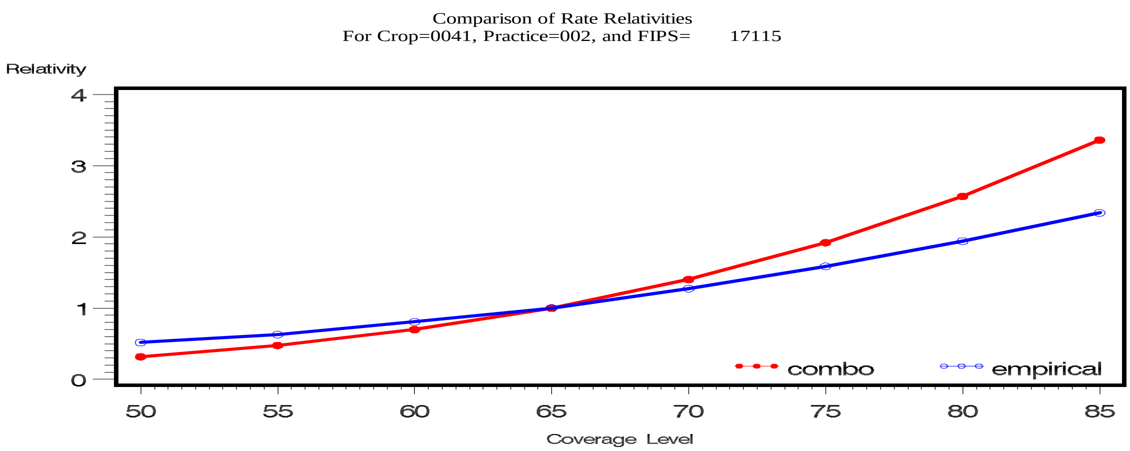
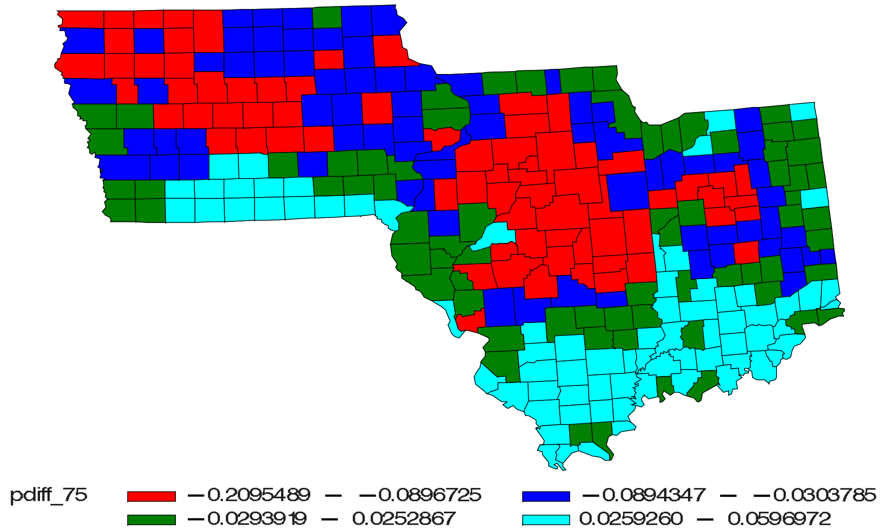


Figure 7.3. Geographic Dispersion of Corn Rate Relativity Differences
A. Corn

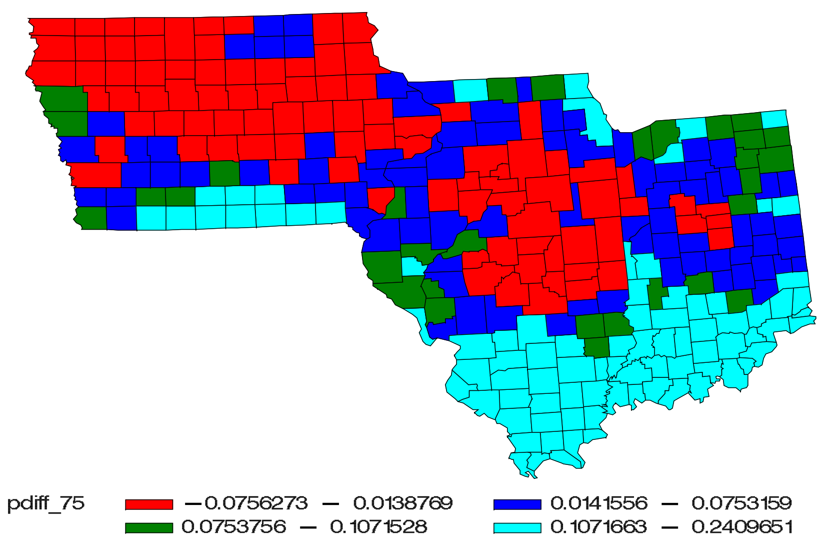
Rate Relativity Percentage Differences
Combo vs. Current Relativities: Non-Irrigated Corn at 75% Coverage



%Difference = (Current Relativity - Combo Relativity)/Current Relativity

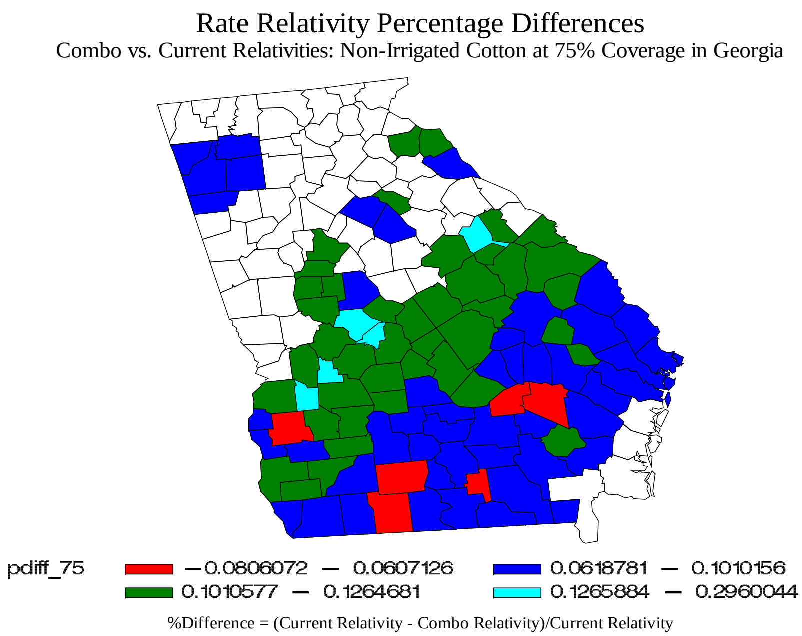
B. Soybeans

Rate Relativity Percentage Differences
Combo vs. Current Relativities: Non-Irrigated Soybeans at 75% Coverage

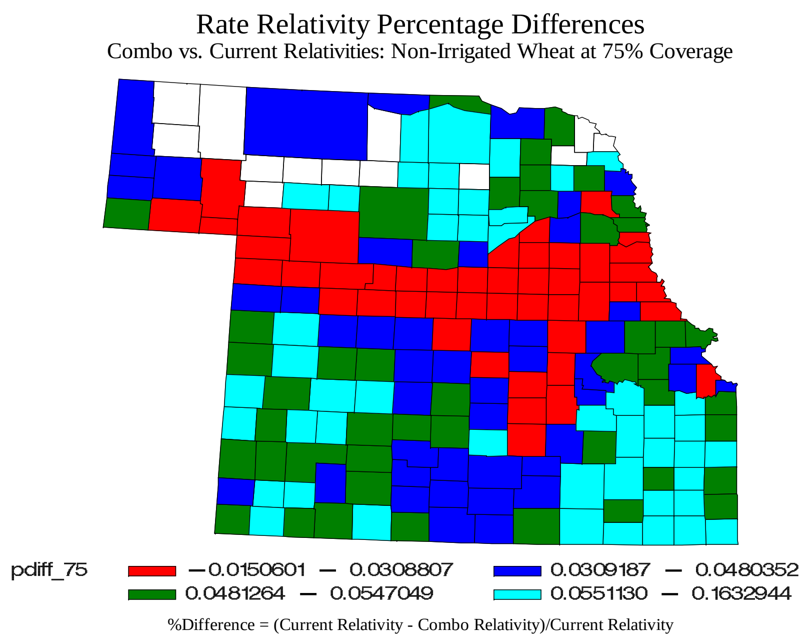


%Difference = (Current Relativity - Combo Relativity)/Current Relativity

Figure 7.4. Geographic Dispersion of Cotton Rate Relativity Differences
A. Cotton



B. Wheat



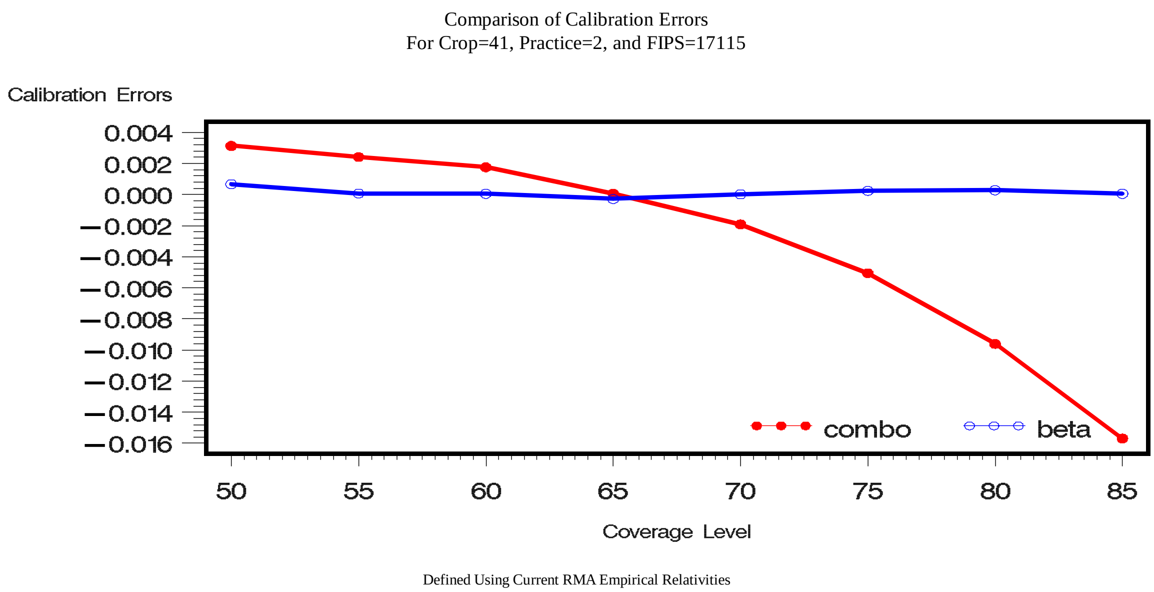
The document entitled “Development of a New Rating Method for Multi-Peril Crop Insurance” argues that the truncated normal distribution proposed for the combo plan closely resembles a beta distribution. However, it is not apparent that the distributions were compared over the entire range of rate relativities inherent in RMA’s current rating process. In order to consider the degree to which calibration errors may characterize a beta density and the truncated normal that is only calibrated to the APH yield and the 65% coverage rate, we conducted an empirical evaluation of the calibration errors for a selected set of crops and counties. We compare the truncated normal, calibrated to the 65% rate and the APH yield, and a four-parameter beta distribution, calibrated across the entire range of rates implied by the current rate relativity structure. Figure 7.5 presents examples of calibration errors across the range of rate relativities for the proposed combo rating method and for a beta that is calibrated to rates at all coverage levels. Although the beta distribution may have a small degree of calibration error at the 65% rate, it tends to provide a much better fit to the range of rate relativities across coverage levels. The differences are more extreme at high coverage levels for the truncated normal.

Finally, perhaps the most critical issue pertains to the extent that the implied revenue loads tend to differ across the alternative rating methods. Using the same selection of counties, we considered the differences in implied revenue loads (without a harvest price option) using the recommended combo methods and a 4-parameter beta distribution calibrated across the range of rate relativities. We assumed 40% volatility and adopted the same general simulation procedures to impose correlation, which we assumed to be -0.40. Figure 7.6 presents examples of the alternative revenue loads. In many cases, the loading factors are very similar. However, differences become apparent at high coverage levels in every case. At the 85% coverage level, the loading factors typically differ by about 1 percentage point, with the combo revenue loads being smaller.

In summary we generally find that the COMBO rating methodology does an appropriate job of combining the various aspects of yield and price risk into a revenue product that provides both a Harvest Price Revenue Rate (HP Rate) and the Harvest Price Exclusion Option Revenue Rate (HPEO Rate). Maintaining consistency between these revenue products and the underlying APH product is not simple. However, we generally concur with the way RMA determines price-yield correlations and price variability. We recommend that RMA consider revising the COMBO rating method to eliminate potential inconsistency in the yield rate relativities applied. Though the differences may be modest in many cases, we believe that a more conceptually sound result would be obtained from applying a consistent set of yield rate relativities across the entire rating process. This could involve calibrating the desired distribution (e.g., censored normal) to the empirical rate relativities currently used by RMA or, alternatively, abandoning these empirical rate relativities in favor of those that emerge from calibration to the APH and a single rate.

Figure 7.5. Examples of Calibration Errors (Defined by Current Rate Relativity Structure) From 4-Parameter Beta Distribution and Censored Normal (Combo Method)

A. Corn



B. Soybeans

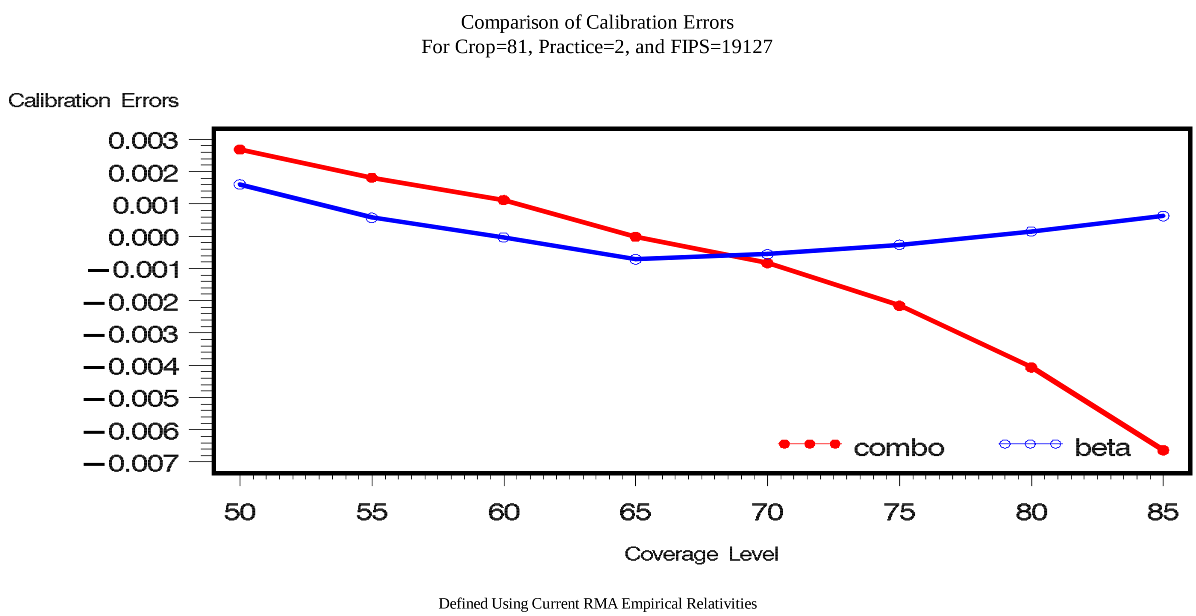
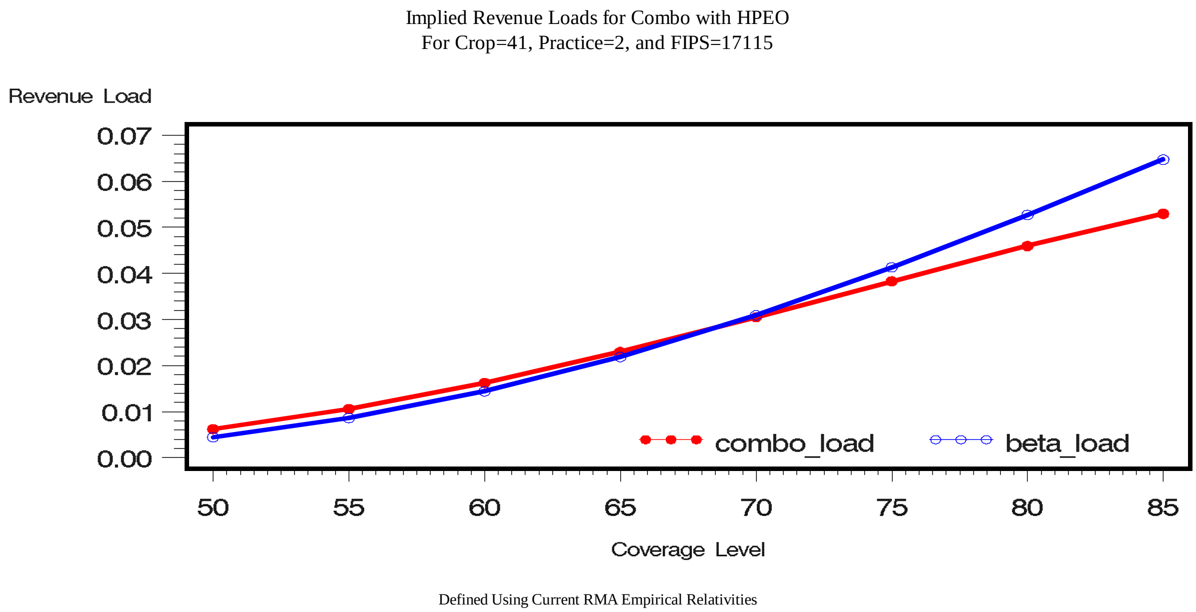
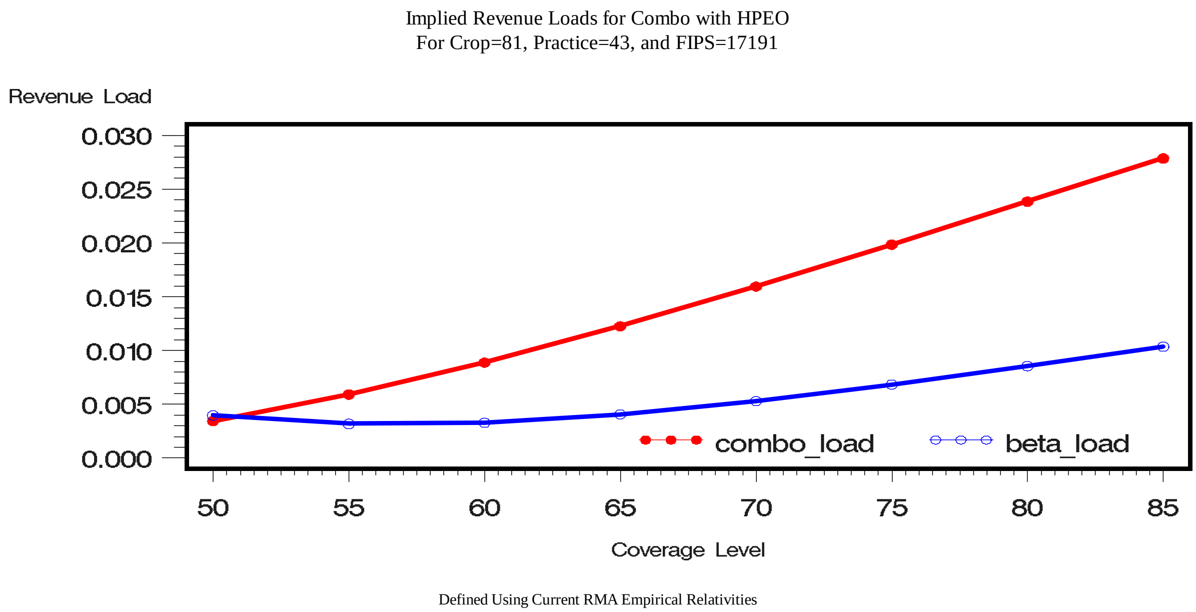


Figure 7.6. Implied Revenue Loads for RA-HPEO Rates From Beta Distribution (Calibrated to Current RMA Rate Relativities) and Censored Normal (Combo Method)

A. Corn



B. Soybeans



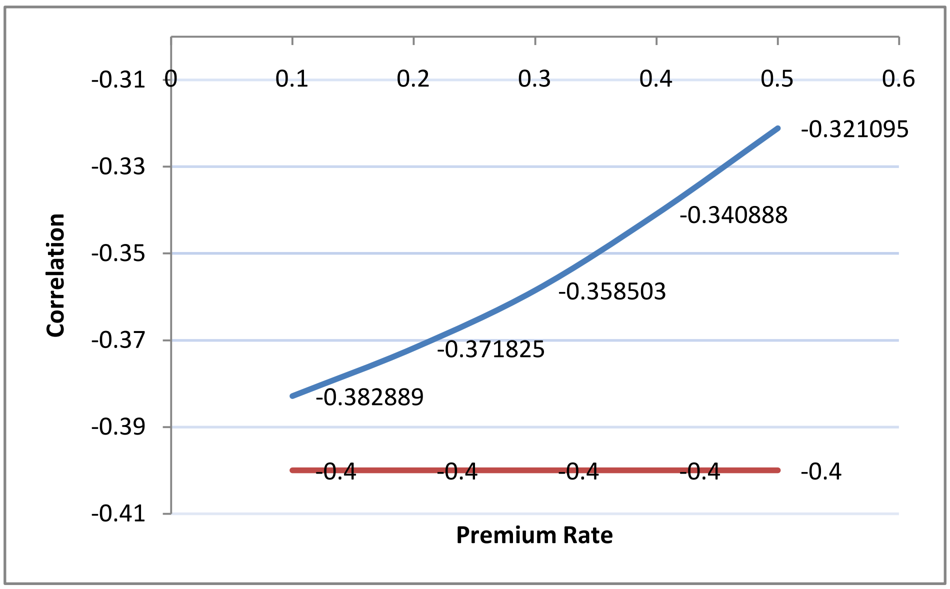
7.3. Minor Comments

Our review and evaluation also suggested a number of other minor points, which are identified here. In no cases are major concerns identified and we suspect that several of these points may simply reflect typographical errors. These are discussed in turn.

1. Depending on the complexity associated with implementation, it may be preferable to adopt direct analytical methods to obtain numerical solutions rather than carrying forward a relatively small number of points taken from a uniform (or the "nearly uniform sequence"). Arguments that point out that some quantile functions do not have closed form solutions are not sufficient to rule out their use (as such is true even of the normal and log-normal quantile functions). Numerical solutions to these problems are readily available (see, for example, the BETAINV function in Excel).
2. The methods used in rating RA involve calibrating a beta pdf to the APH yield and 65% rate. However, it was noted that the beta may be difficult to implement in practice, which is why a censored normal pdf is recommended in the combo rating method. While we acknowledge that it can be difficult to calibrate a beta distribution in some cases (primarily in cases involving very high premium rates), we do not necessarily agree that the beta is not appropriate for a wide range of county/crop programs. While it is true that the beta quantile function (inverse cdf) may not have a closed form solution, the same is true for the normal and log-normal distributions and thus reliance upon numerical solutions for working with the quantile functions does not seem to be a significant barrier to using the beta density.
3. While one must be sensitive to the fact that it is difficult to measure yield-price correlations with relatively limited data and constantly shifting programs, a number of questions regarding the assumed correlations are relevant. First, it seems more likely that farm program changes (e.g., planting flexibility) that occurred with the 1996 FAIR Act would have significantly shifted correlations. Thus, using data since 1990 may also raise questions. Perceived changes in correlation over time which serve to support arguments for changing these correlations in the rating model are based upon very short series and are unlikely to provide statistically significant differences.
4. We suggest that RMA evaluate estimating price-yield correlations at a level below the state level as there may be clear reason to allow correlation to vary across production regions in a state. For example, irrigated corn in western Kansas may have a very different price-yield correlation than in the eastern portion of the state.
5. In cases where an excessive degree of censoring/truncation of the normal distribution is needed to adequately calibrate the rate and yield, the correlation structure can be significantly altered when considering the $y=\max(0, y_i)$ correlation with price. Put differently, a lower degree of correlation will exist for the censored variable with price than was the case for the uncensored variable. How

this is addressed in the rating simulation is unclear. Figure 7.7 below illustrates this phenomenon (where the blue line is for the censored case and the red line for the uncensored case). At low premium rates, no distortion occurs. However, at very high premium rates, a much lower degree of correlation is obtained for the truncated yield. We do not think this is a significant issue in that rates high enough to induce such distortions are unlikely to be observed in areas that have substantial price-yield correlation.

Figure 7.7. Distortion in Correlation from Using Truncation of Normal Distribution (True Correlation = -0.40)



8.0 Summary of Recommendations

This chapter summarizes and consolidates our recommendations for APH and COMBO rating. For additional details see chapter six for a detailed explanation of recommendations for the APH product. Chapter seven provides the explanation of our recommendations for COMBO rating.

8.1 Basic Approach to APH rating

We recommend that RMA continue to use loss experience as the foundation of the rating system as it is the only way to assure that actual losses drive the rating results. This is consistent with standard property and casualty insurance rating practices. While crop insurance poses a unique set of actuarial challenges, alternatives to loss-experience-based rating would likely fail to adequately address the multiple objectives imposed on the APH program.

8.2 Reference Rate, Reference Yield and Exponent

We recommend that RMA adopt updated reference yields which are congruent with reference rates and exponents. This is a critical step in obtaining appropriate rates for insured units at all yield levels. These updated reference yields would be based upon APH data so that the reference yield and reference rate are 'centered' within a county's book of business.

Based on our review of the yield ratio curve and the rating exponent, we recommend that RMA conduct analysis to update these parameters of the rating formula. Given the heavy censoring of loss cost ratios at zero, we suggest that the RMA investigate the usefulness of nonlinear censored regression approaches or other parametric or semiparametric censored regression models, rather than NLS, for use in this estimation process.

8.3 Type and Practice Factors

Based on our analysis, we recommend that the RMA modify its procedures so that the type and practice factors are applied to the State Catastrophic Rate Load portion of the target rate. Further, we recommend that RMA rebase its rates and type/practice factors to a common type/practice to improve the transparency of the rating structure.

We recommend that RMA adjust prior experience for the actual or estimated mix by type and practice.

8.4 Unit Factor

We recommend that RMA adopt procedures for developing target rates that incorporate unit factors that are consistent with the actual mix of unit structures in the historical loss experience.

8.5 Catastrophic Loading

We recommend that RMA eliminate the coverage approximation procedure and adjust all experience to the 50% coverage level when low coverage levels make up a significant proportion of experience. Published base rates could still be maintained at the 65% coverage level simply by dividing the 50% pure premium by the 50% coverage level adjustment factor. We recognize this would place greater reliance on the estimated coverage level relativities. However, we believe these can be effectively estimated for the major crops.

8.6 Catastrophic Loading

We recommend that RMA re-evaluate the catastrophic loading procedure and reduce the degree to which cat loading influences rates in low risk regions. Having said this, we generally support maintaining state/crop catastrophic loading boundaries, unless one is addressing a crop with geographically-sparse participation.

8.7 Use of Expert Judgment

We recommend that if, in fact, local conditions have changed such that an existing, credible time series of data is not appropriate for rating, an explicit discussion of the changes should accompany a plan to either adjust the prior data or to set a rate through judgment that will then be adjusted using standard methods as new data become available. Regional offices of the RMA should play an important role in any such process. The decision and results should be documented, transparent, and reviewable by outside parties.

8.8 Additional Rating Variables

We recommend a comprehensive study to evaluate utilizing soil and other site specific information for the purposes of refining and individualizing rates. We also suggest RMA consider defining and collecting additional type and practice data for characteristics that likely affect insurance risk levels.

8.9 Statewide Rate Level Adequacy

We recommend that RMA evaluate the extent to which statewide rate levels may be inadequate due to capping and, if such inadequacies are significant, consider the use of an inadequacy off-balance. We recommend that RMA consider re-evaluating whether the minimum load is appropriate in light of the additional reserve loading.

8.10 Yield Correlation and Weighting Loss Experience Data

We recommend that RMA evaluate alternative loss cost experience weighting methods. Our analysis suggests it is feasible to incorporate additional weather information into the rating system and to allow additional weight be placed on more credible annual observations. However, we do not offer specific recommendations for changing the manner in which experience is weighted over time in current rating methods. We believe a detailed study of this issue should investigate optimal weights and that implementation issues should be assessed.

8.11 Study of Loss Ratio Rating System

We recommend that RMA undertake a comprehensive study of the loss ratio method for determining future rate changes, perhaps in conjunction with a study aimed at a State level, top-down approach as recommended by Milliman (2008).

8.12 Combo Rating

We generally find that the COMBO rating methodology does an appropriate job of combining the various aspects of yield and price risk into a revenue product that provides both a Harvest Price Revenue Rate (HP Rate) and the Harvest Price Exclusion Option Revenue Rate (HPEO Rate). Maintaining consistency between these revenue products and the underlying APH product is not simple. However, we generally concur with the way RMA determines price-yield correlations and price variability. We recommend that RMA consider revising the COMBO rating method to eliminate potential inconsistency in the yield rate relativities applied. Though the differences may be modest in many cases, we believe that a more conceptually sound result would be obtained from applying a consistent set of yield rate relativities across the entire rating process. This could involve calibrating the desired distribution (e.g., censored normal) to the empirical rate relativities currently used by RMA or, alternatively, abandoning these empirical rate relativities in favor of those that emerge from calibration to the APH and a single rate.

Review Team Biographies

Keith H. Coble, Ph. D.

Dr. Keith H. Coble is W.L. Giles Distinguished Professor in the Agricultural Economics Department at Mississippi State University. He received his Ph.D. in Agricultural Economics from Texas A&M University in 1993. Coble's background in the area of risk management has encompassed both academic and government experience. Dr. Coble came to Mississippi State after serving as leader of the Crop Risk Management Team at the Economic Research Service of the U.S. Department of Agriculture.

Coble's crop insurance research has included investigation of adverse selection, moral hazard, and crop insurance demand. Coble has also conducted research examining the modeling of price and yield risk, which is fundamental to insurance rating. Coble's work also addressed farmer behavior in response to risk, commodity program and farm bill analysis and in-depth studies the interaction between risk management tools. Dr. Coble is also co-author of a chapter on crop insurance in a book (editors R. Just and R.D. Pope) entitled: *A Comprehensive Assessment of the Role of Risk in U.S. Agriculture.* He was also commissioned by the OECD in 2008 to co-author *An Assessment of Risk Exposure in Agriculture*. Coble has testified before Congressional Committees regarding risk policy on three occasions. His research has covered a broad set of risk and crop insurance issues and has authored or co-authored 56 journal articles, 4 book chapters, 45 reports for government agencies, and 90 scientific meetings papers.

Coble's professional activities include having served as the Chair of the Food and Agricultural Marketing Section. He is also the current Chair of the new Applied Risk Analysis Section of the Agricultural and Applied Economics Association and is an Associate Editor of the *American Journal of Agricultural Economics.*

Dr. Coble has performed numerous analyses for the Federal Crop Insurance Corporation and Risk Management Agency, including serving as an underwriting reviewer and technical expert for the Board of Directors of the Federal Crop Insurance Corporation. Among the other issues he has examined for the RMA include a comparisons of CRC and RA crop insurance rates, Alternative catastrophic loading procedures, Evaluation of cotton crop insurance on cotton acreage, Actuarially fair premium rate adjustments for optional versus basic units, Rate adjustments for farms with different mean (APH) yields, Performance-based discounts for crop insurance, Unit rate factors, An evaluation of county yield trend estimation procedures, and a review of the cotton program.

Thomas O. Knight, Ph. D.

Thomas O. Knight is a Professor in the Department of Agricultural and Applied Economics at Texas Tech University. Prior to joining the Texas Tech faculty in 2002, he was an assistant, associate, and full professor in the Department of Agricultural Economics at Texas A&M University. Dr. Knight was educated at Oklahoma State University, where he completed B.S. (1975) and M.S. (1977) degrees in Agricultural Economics, and at the University of Missouri, where he earned a Ph.D. in Agricultural Economics in 1984.

Throughout his academic career, Dr. Knight's research and teaching programs have focused on agricultural risk and policy analysis. His work has been published widely in scholarly journals, book chapters, Experiment Station, and the popular press. Since 1990, Dr. Knight's research has focused on a wide range of issues relating to the Federal Crop Insurance Program. Among his journal publications are studies on crop insurance demand (*American Journal of Agricultural Economics*, 1996; *Journal of Agricultural and Applied Economics*, 2008), moral hazard in crop insurance programs (*American Journal of Agricultural Economics*, 1997), unit structure premium rate differentials (*Journal of Agricultural and Applied Economics*, 1999; *American Journal of Agricultural Economics*, forthcoming 2010), and experience-based premium rate discounts (*American Journal of Agricultural Economics*, 2006). Dr. Knight has served as an instructor for a seminar on crop insurance issues presented for U.S. House of Representatives staff members and testified before the U.S. House of Representatives Agriculture Committee's Subcommittee on General Farm Commodities and Risk Management.

While on faculty at Texas A&M University, Dr. Knight received the Deputy Chancellor's Award for Excellence in Team Research and the Department of Agricultural Economics, Graduate Student Association's Award for Graduate Teaching. At Texas Tech University, he has received the College of Agricultural Sciences and Natural Resources Research Award and the university-wide Faculty Recognition Award presented jointly by the Mortar Board and Omicron Delta Kappa senior honor societies.

Dr. Knight also serves as an advisor to the Board of Directors of the Federal Crop Insurance Corporation and to the Risk Management Agency. He has conducted underwriting reviews of eighteen plans of insurance under consideration by the FCIC Board. He has also led or collaborated in six major program reviews for the FCIC Board and the RMA. These reviews have focused on: revenue insurance product premium rates and coverage level differentials, cotton acreage effects of crop insurance programs; actuarial soundness and product design of cotton insurance programs; a comprehensive review of the Dollar Plan insurance product design; a comprehensive review of the GRP pilot insurance program; and a comprehensive review of the AGR pilot insurance program.

Barry K. Goodwin, Ph. D.

Barry K. Goodwin is currently William Neal Reynolds Distinguished Professor with joint appointments in the Department of Agricultural and Resource Economics and the Department of Economics at North Carolina State University. He previously held the Andersons Endowed Chair in the Department of Agricultural, Environmental, and Resource Economics at the Ohio State University. He also was assistant and associate professor in the Department of Agricultural Economics at Kansas State University. He holds a Ph.D. degree in Economics and a minor in Statistics from North Carolina State University.

Goodwin has received numerous professional achievement awards. He is a Fellow of the Applied and Agricultural Economics Association (AAEA), which is the highest professional award in agricultural economics. He has received "Best Published Paper" awards for papers published in the *American Journal of Agricultural Economics*, the *Journal of Agricultural and Resource Economics*, and the *Canadian Journal of Agricultural Economics*. He has published approximately 115 refereed journal articles and book chapters and has co-authored three books, including the widely cited text "The Economics of Crop Insurance and Disaster Assistance." He was named to Who's Who in Economics, and was named one of the "Top 1000 Most Cited Economists, 1990-2000 (#644)," one of the "Top Published Economists by Article Counts, 1990-2000 (#118, #156)," and one of the "Top Published Economists by Page Counts, 1990-2000 (#378)." He has done extensive research and consulting on issues related to crop insurance and risk management.

Mary Frances Miller, FCAS, MAAA, Hon FIA, CPCU, ARe, AIM

Mrs. Miller is a founder and the senior consulting actuary with Select Actuarial Services. With more than 20 years of property and casualty actuarial experience, she provides actuarial consulting services on several major accounts and is additionally responsible for the professional development of the other members. Her expertise is frequently called upon to assist clients in making decisions regarding the maintenance and design of their risk management programs.

Prior to the formation of Select Actuarial Services, Mrs. Miller was the Senior Vice President and Chief Actuary for five years at Sedgwick Actuarial Services. As Chief Actuary she performed a wide spectrum of actuarial studies and also managed the actuarial staff. Before joining Sedgwick in 1993, Mrs. Miller was reinsurance actuary with American States Insurance Companies, where her duties included pricing within the Reinsurance Division, as well as the design and development of specialized software targeting property catastrophe exposures, case reserving for automobile and workers' compensation long-term disability claims, and evaluating treaty commutation proposals.

Mrs. Miller graduated with highest honor from the Honors College at Michigan State University with Bachelor of Arts degrees in Mathematics and Linguistics. She is a Fellow of the Casualty Actuarial Society, a member of the American Academy of Actuaries and a Chartered Property and Casualty Underwriter. She was elected an Honorary Fellow of the Institute of Actuaries (UK) in 2005. She has been an active contributor to the actuarial profession since achieving fellowship in 1988, and has chaired the CAS Professionalism Education Committee, the Education Policy Committee, and task forces on mutual recognition and future education planning. She was Vice-President for Admissions of the Casualty Actuarial Society from 2000 to 2002, President-Elect in 2003, President in 2004, and she chaired the CAS Board in 2005. She has been a member of the Boards of Directors of the American Academy of Actuaries and the Conference of Consulting Actuaries and currently serves on the Academy's Committee on Qualifications and its Casualty Practice and Professionalism Councils. As a member of the Actuarial Standards Board subcommittee on reserves, Mrs. Miller was a drafter of the United States standards of practice for reserve opinions (#36) and unpaid claim estimates (#43). She currently chairs the International Actuarial Association's Education Committee.

Mrs. Miller has been elected President-Elect of the American Academy of Actuaries for 2010 and will serve as the Academy's President in 2011.

Roderick M. Rejesus, Ph.D.

Dr. Roderick M. Rejesus is an assistant professor of agricultural and resource economics at North Carolina State University. Prior to his current position, Dr. Rejesus was an assistant professor in the agricultural and applied economics department at Texas Tech University. Dr. Rejesus received his M.S. degree at Clemson University and his Ph.D. degree at the University of Illinois at Urbana-Champaign, both in Agricultural Economics. He has an active research and extension program that focuses on crop insurance and applied production economics.

Dr. Rejesus has published research findings on ex-post moral hazard in crop insurance, determinants of anomalous prevented planting claims in crop insurance, farmer preferences for risk management information sources, and agricultural risk management tool utilization. He has been involved in several RMA funded projects, namely: Unit Division Structure Review, Premium Rate Discount Project, and the Reference Yield Update Methodology Project. In addition, he has participated in several reviews of proposed pilot insurance products and underwriting procedures submitted for consideration to the Board of Directors of the FCIC.

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Appendix

Data for Figures and Maps in the Report

Appendix Table 1

Data for Table 5.1

LR_10	LR_24	LR_40	TRUE
1.574358	0.709215	0.87794	1
1.574358	0.709215	0.87794	1
1.574358	0.709215	0.678011	1
1.574358	0.709215	0.678011	1
1.574358	0.709215	0.678011	1
0	0.709215	0.678011	1
0	0.709215	0.678011	1
0	0.709215	0.595098	1
0	0.686896	0.5856	1
0	0.686896	0.5856	1
0	0.686896	0.5856	1
0	0.524817	0.5856	1
0.029932	0.534787	0.591563	1
0.029932	0.534787	0.591563	1
0.029932	0.534787	0.431487	1
0.029932	0.534787	0.431487	1
0.029932	0.534787	0.431487	1
0.029932	0.534787	0.431487	1
0.029932	0.534787	0.431487	1
1.815225	1.129885	0.788569	1
1.785293	1.129885	0.788569	1
1.785293	0.605067	0.788569	1
1.785293	0.605067	0.788569	1
2.841621	0.957177	0.999835	1
2.841621	0.957177	0.986448	1
2.841621	0.957177	0.986448	1
2.841621	0.957177	0.986448	1
1.056328	0.957177	0.889206	1
1.056328	0.957177	0.889206	1
1.056328	0.957177	0.889206	1
1.056328	0.957177	0.889206	1
0	0.957177	0.889206	1
0	0.957177	0.889206	1
0	0.957177	0.889206	1
0.269621	1.047089	0.943153	1
0.269621	1.047089	0.943153	1
0.269621	1.037144	0.943153	1

0.269621	1.037144	0.628258	1
1.602404	1.481334	0.894768	1
1.602404	1.481334	0.894768	1
1.602404	1.481334	0.894768	1
1.602404	1.481334	0.894768	1
1.332548	1.481334	0.894768	1
1.332548	0.886213	0.894768	1
1.332548	0.886213	0.894768	1
1.332548	0.886213	0.894768	1
0	0.886213	0.894768	1
0	0.534103	0.894768	1
0	0.534103	0.894768	1
0	0.534103	0.894768	1
0	0.534103	0.894768	1
0	0.534103	0.894768	1
0	0.534103	0.888805	1
0	0.534103	0.888805	1
0	0.534103	0.888805	1
1.8428	1.148362	1.257365	1
3.212821	1.605044	1.531346	1
3.212821	1.605044	1.531346	1
3.212821	1.515131	1.531346	1
3.212821	1.515131	1.174287	1

Appendix Table 2. Soybean and Corn Acreage Insured by Year

(Data for Figures 6.1 and 6.2)

	Corn				Soybeans			
	Total	**IL**	**IN**	**IA**	**Total**	**IL**	**IN**	**IA**
1981	4.707	0.599	0.308	3.800	2.285	0.420	0.195	1.670
1982	3.330	0.491	0.330	2.509	1.998	0.375	0.254	1.368
1983	1.655	0.252	0.158	1.245	1.524	0.280	0.150	1.094
1984	4.971	0.946	0.717	3.308	2.843	0.632	0.437	1.774
1985	5.827	1.126	0.832	3.869	3.045	0.691	0.403	1.952
1986	5.648	1.249	0.689	3.709	3.328	0.783	0.356	2.189
1987	5.235	1.217	0.613	3.405	3.594	0.884	0.364	2.347
1988	5.847	1.282	0.656	3.910	3.708	0.846	0.383	2.480
1989	15.511	4.996	1.332	9.183	9.136	2.986	1.089	5.061
1990	12.429	3.513	1.122	7.794	6.730	1.988	0.720	4.022
1991	9.731	2.868	1.031	5.832	5.889	1.710	0.668	3.511
1992	11.010	3.548	1.370	6.092	6.081	2.063	0.785	3.232
1993	9.917	3.247	1.244	5.425	5.948	1.985	0.758	3.205
1994	12.203	3.672	1.355	7.177	7.145	2.276	0.797	4.071
1995	23.385	8.727	3.926	10.732	19.849	8.080	3.382	8.386
1996	16.281	7.370	2.710	6.201	14.500	6.465	2.579	5.456
1997	18.243	6.467	2.423	9.353	15.892	5.668	2.090	8.134
1998	18.178	6.294	2.318	9.566	16.208	5.833	2.244	8.131
1999	19.002	6.855	2.616	9.530	17.478	6.304	2.451	8.723
2000	20.228	7.334	2.938	9.956	18.286	6.635	2.771	8.880
2001	19.644	7.156	2.872	9.616	18.617	6.603	2.833	9.182
2002	20.162	7.195	2.851	10.117	18.104	6.422	2.931	8.750
2003	20.537	7.397	3.035	10.106	17.874	6.244	2.775	8.855
2004	20.859	7.395	2.991	10.473	16.991	5.811	2.708	8.472
2005	20.624	7.377	2.948	10.299	16.507	5.614	2.635	8.259
2006	18.192	5.584	2.580	10.028	16.563	5.552	2.662	8.349
2007	21.651	7.076	3.152	11.424	13.837	4.534	2.182	7.121
2008	21.423	7.432	2.965	11.027	16.488	5.498	2.684	8.306

Appendix Table 3. Correlation and Effective Number of Observations

(Data from Figure 6.3)

	50	25	10	5
	Groups of	Groups of	Groups of	Groups of
Correlation	2	4	10	20
0.95	52.56	26.97	10.96	5.51
0.90	55.25	29.15	12.06	6.10
0.85	58.06	31.57	13.33	6.79
0.80	60.98	34.25	14.79	7.60
0.75	64.00	37.21	16.49	8.56
0.70	67.11	40.49	18.48	9.70
0.65	70.30	44.10	20.82	11.08
0.60	73.53	48.08	23.58	12.76
0.55	76.78	52.42	26.86	14.82
0.50	80.00	57.14	30.77	17.39
0.45	83.16	62.21	35.43	20.63
0.40	86.21	67.57	40.98	24.75
0.35	89.09	73.13	47.56	30.05
0.30	91.74	78.74	55.25	36.90
0.25	94.12	84.21	64.00	45.71
0.20	96.15	89.29	73.53	56.82
0.15	97.80	93.68	83.16	70.05
0.10	99.01	97.09	91.74	84.03
0.05	99.75	99.26	97.80	95.47
0.00	100.00	100.00	100.00	100.00

Appendix Table 4. Values of Palmer's Z Index

(Data from Figure 6.4)

Year	IL	IN	IA
1970	-0.28	0.85	-0.47
1971	1.96	1.96	0.13
1972	0.46	-0.11	2.92
1973	1.38	1.99	1.85
1974	-2.34	-3.21	-2.05
1975	-0.09	-1.53	-3.38
1976	-0.39	0.11	-1.75
1977	-0.62	-0.96	-1.05
1978	1.2	1.54	2.99
1979	2.29	5.86	1.62
1980	-1.18	0.06	-1.76
1981	3.63	1.55	1.92
1982	2.94	-0.08	3.29
1983	-2.46	-2.56	-1.79
1984	-0.62	-0.04	0.85
1985	-0.01	-0.69	-1.25
1986	2.17	1.98	1.63
1987	0.06	1.6	1.12
1988	-2.47	-0.77	-3.27
1989	-0.15	2.03	-1.15
1990	1.06	1.77	3.83
1991	-2.65	-2.7	-1.68
1992	4.18	6.49	6.19
1993	3.43	0.78	9.4
1994	-1.04	-0.3	0.9
1995	-0.74	-1.26	-0.22
1996	1.59	2.16	0.11
1997	-1.57	-0.81	-0.8
1998	-0.05	1.72	-0.52
1999	-1.26	-1.92	1.96
2000	1.53	0.55	1.02
2001	0.34	2.56	-0.68
2002	-1.57	-1.89	0.15
2003	1.84	6.31	0.92
2004	0.9	2.26	1.36
2005	-1.32	0.45	-0.5
2006	0.28	1.71	-1.51

2007	-0.16	-0.72	-0.46
2008	2.94	0.89	3.05

Appendix Table 5. Frequency Distribution of Palmer's Z in Indiana

(Data for Figure 6.5)

Palmer's Z	Frequency
-4.5	0.0088
-3.5	0.0439
-2.5	0.0702
-1.5	0.1053
-0.5	0.1842
0.5	0.2368
1.5	0.1140
2.5	0.1667
3.5	0.0175
4.5	0.0088
5.5	0.0439

Appendix Table 6. Comparison of Combo and Empirical Rate Relativities

(Data from Figures 7.1 and 7.2)

Crop	Practice	FIPS	Cov Lev	Combo	Empirical
11	4	20057	50	0.8513	0.7880
11	4	20057	55	0.8992	0.8340
11	4	20057	60	0.9488	0.8990
11	4	20057	65	1.0000	1.0000
11	4	20057	70	1.0528	1.1932
11	4	20057	75	1.1071	1.4619
11	4	20057	80	1.1628	1.7964
11	4	20057	85	1.2198	2.0545
21	2	28143	50	0.5196	0.7480
21	2	28143	55	0.6523	0.8250
21	2	28143	60	0.8116	0.9090
21	2	28143	65	1.0000	1.0000
21	2	28143	70	1.2199	1.1584
21	2	28143	75	1.4730	1.3353
21	2	28143	80	1.7602	1.5308
21	2	28143	85	2.0818	1.7812
21	2	48357	50	0.9470	0.7850
21	2	48357	55	0.9640	0.8320
21	2	48357	60	0.9810	0.9060
21	2	48357	65	0.9981	1.0000
21	2	48357	70	1.0152	1.1900
21	2	48357	75	1.0323	1.4530
21	2	48357	80	1.0495	1.7778
21	2	48357	85	1.0667	2.1777
41	2	17115	50	0.3163	0.5160
41	2	17115	55	0.4749	0.6280
41	2	17115	60	0.6972	0.8070
41	2	17115	65	1.0000	1.0000
41	2	17115	70	1.4014	1.2734
41	2	17115	75	1.9186	1.5862
41	2	17115	80	2.5668	1.9397
41	2	17115	85	3.3573	2.3363

Appendix Table 7. Geographic Dispersion of Rate Relativity Differences

(Data from Figures 7.3 and 7.4)

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
11	20	1	0.0653	CYAN
11	20	3	0.0640	CYAN
11	20	5	0.0460	BLUE
11	20	7	0.0450	BLUE
11	20	9	0.0519	GREEN
11	20	11	0.0536	GREEN
11	20	13	0.0524	GREEN
11	20	15	0.0618	CYAN
11	20	17	0.0488	GREEN
11	20	19	0.0636	CYAN
11	20	21	0.0645	CYAN
11	20	23	0.0582	CYAN
11	20	25	0.0900	CYAN
11	20	27	0.0221	RED
11	20	29	0.0401	BLUE
11	20	31	0.0654	CYAN
11	20	33	0.0532	GREEN
11	20	35	0.0606	CYAN
11	20	37	0.0539	GREEN
11	20	39	0.0597	CYAN
11	20	41	0.0290	RED
11	20	43	0.0542	GREEN
11	20	45	0.0574	CYAN
11	20	47	0.0672	CYAN
11	20	49	0.0534	GREEN
11	20	51	0.0460	BLUE
11	20	53	0.0412	BLUE
11	20	55	0.0512	GREEN
11	20	57	0.1467	CYAN
11	20	59	0.0627	CYAN
11	20	61	0.0455	BLUE
11	20	63	0.0770	CYAN
11	20	65	0.0588	CYAN
11	20	67	0.0643	CYAN
11	20	69	0.1199	CYAN
11	20	71	0.0789	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
11	20	73	0.0561	CYAN
11	20	75	0.0501	GREEN
11	20	77	0.0442	BLUE
11	20	79	0.0309	BLUE
11	20	81	0.0619	CYAN
11	20	83	0.0825	CYAN
11	20	85	0.0507	GREEN
11	20	87	0.0457	BLUE
11	20	89	0.0376	BLUE
11	20	91	0.0532	GREEN
11	20	93	0.0510	GREEN
11	20	95	0.0337	BLUE
11	20	97	0.0492	GREEN
11	20	99	0.0625	CYAN
11	20	101	0.1277	CYAN
11	20	103	0.0303	RED
11	20	105	0.0398	BLUE
11	20	107	0.0601	CYAN
11	20	109	0.0640	CYAN
11	20	111	0.0659	CYAN
11	20	113	0.0234	RED
11	20	115	0.0344	BLUE
11	20	117	0.0333	BLUE
11	20	119	0.0774	CYAN
11	20	121	0.0513	GREEN
11	20	123	0.0309	RED
11	20	125	0.0656	CYAN
11	20	127	0.0607	CYAN
11	20	129	0.0505	GREEN
11	20	131	0.0502	GREEN
11	20	133	0.0655	CYAN
11	20	135	0.0574	CYAN
11	20	137	0.0583	CYAN
11	20	139	0.0637	CYAN
11	20	141	0.0405	BLUE
11	20	143	0.0277	RED
11	20	145	0.0480	BLUE
11	20	147	0.0447	BLUE
11	20	149	0.0491	GREEN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
11	20	151	0.0416	BLUE
11	20	153	0.0659	CYAN
11	20	155	0.0405	BLUE
11	20	157	0.0354	BLUE
11	20	159	0.0597	CYAN
11	20	161	0.0385	BLUE
11	20	163	0.0479	BLUE
11	20	165	0.0576	CYAN
11	20	167	0.0538	GREEN
11	20	169	0.0233	RED
11	20	171	0.1160	CYAN
11	20	173	0.0389	BLUE
11	20	175	0.0512	GREEN
11	20	177	0.0517	GREEN
11	20	179	0.0580	CYAN
11	20	181	0.0656	CYAN
11	20	183	0.0309	BLUE
11	20	185	0.0447	BLUE
11	20	187	0.0473	BLUE
11	20	189	0.0668	CYAN
11	20	191	0.0528	GREEN
11	20	193	0.0663	CYAN
11	20	195	0.0615	CYAN
11	20	197	0.0581	CYAN
11	20	199	0.1088	CYAN
11	20	201	0.0290	RED
11	20	203	0.0788	CYAN
11	20	205	0.0657	CYAN
11	20	207	0.0532	GREEN
11	20	209	0.0472	BLUE
11	31	1	0.0171	RED
11	31	3	0.0576	CYAN
11	31	7	0.0698	CYAN
11	31	11	0.0537	GREEN
11	31	15	0.0530	GREEN
11	31	19	0.0495	GREEN
11	31	21	0.0464	BLUE
11	31	23	0.0434	BLUE
11	31	25	0.0204	RED

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
11	31	27	0.0545	GREEN
11	31	29	0.0429	BLUE
11	31	31	0.0323	BLUE
11	31	33	0.0594	CYAN
11	31	35	0.0186	RED
11	31	37	0.0457	BLUE
11	31	39	0.0511	GREEN
11	31	41	0.0645	CYAN
11	31	47	0.0793	CYAN
11	31	49	0.0337	BLUE
11	31	53	0.0236	RED
11	31	55	0.0547	CYAN
11	31	57	0.0636	CYAN
11	31	59	0.0175	RED
11	31	61	0.0170	RED
11	31	63	0.0408	BLUE
11	31	65	0.0261	RED
11	31	67	0.0294	RED
11	31	69	0.0565	CYAN
11	31	71	0.0749	CYAN
11	31	73	-0.0112	RED
11	31	77	0.0775	CYAN
11	31	79	0.0480	BLUE
11	31	81	0.0272	RED
11	31	83	0.0052	RED
11	31	85	0.0379	BLUE
11	31	87	0.0404	BLUE
11	31	89	0.1407	CYAN
11	31	93	0.0560	CYAN
11	31	95	0.0120	RED
11	31	97	0.0144	RED
11	31	99	-0.0218	RED
11	31	101	0.0348	BLUE
11	31	103	0.0448	BLUE
11	31	105	0.0832	CYAN
11	31	107	0.0380	BLUE
11	31	109	0.0129	RED
11	31	111	0.0433	BLUE
11	31	113	0.0913	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
11	31	115	0.0616	CYAN
11	31	117	0.0553	CYAN
11	31	119	0.0519	GREEN
11	31	121	0.1624	CYAN
11	31	123	0.1138	CYAN
11	31	125	0.0655	CYAN
11	31	127	0.0184	RED
11	31	129	0.0100	RED
11	31	131	0.0285	RED
11	31	133	0.0313	BLUE
11	31	135	0.0559	CYAN
11	31	137	0.0240	RED
11	31	139	0.0513	GREEN
11	31	141	0.0490	GREEN
11	31	143	0.0238	RED
11	31	145	0.0254	RED
11	31	147	0.0240	RED
11	31	149	0.1633	CYAN
11	31	151	0.0149	RED
11	31	153	0.0001	RED
11	31	155	0.0486	GREEN
11	31	157	0.0830	CYAN
11	31	159	0.0216	RED
11	31	163	0.0722	CYAN
11	31	165	0.0891	CYAN
11	31	167	0.0551	CYAN
11	31	169	0.0051	RED
11	31	173	0.0561	CYAN
11	31	175	0.0811	CYAN
11	31	177	0.0514	GREEN
11	31	181	-0.0095	RED
11	31	185	0.0127	RED
21	13	7	0.1057	GREEN
21	13	19	0.0943	BLUE
21	13	27	0.0840	BLUE
21	13	29	0.0782	BLUE
21	13	69	0.0831	BLUE
21	13	103	0.0799	BLUE
21	13	129	0.0771	BLUE

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
21	13	165	0.1027	GREEN
21	13	171	0.1072	GREEN
21	13	175	0.1024	GREEN
21	13	205	0.0931	BLUE
21	13	209	0.0808	BLUE
21	13	249	0.2410	CYAN
21	13	261	0.1069	GREEN
21	13	271	0.1038	GREEN
21	13	279	0.0822	BLUE
21	13	287	0.0861	BLUE
21	13	307	0.1346	CYAN
21	13	309	0.0963	BLUE
21	13	319	0.1070	GREEN
21	28	1	0.0204	RED
21	28	9	0.0403	RED
21	28	11	0.0266	RED
21	28	13	0.0123	RED
21	28	15	-0.0160	RED
21	28	35	0.0761	BLUE
21	28	43	0.0544	RED
21	28	49	0.0634	BLUE
21	28	81	0.0994	BLUE
21	28	89	-0.0806	RED
21	28	95	0.1812	CYAN
21	28	139	0.0474	RED
21	28	141	0.0314	RED
21	28	143	-0.0338	RED
21	28	151	0.0512	RED
21	28	155	0.1231	GREEN
21	28	159	0.1636	CYAN
21	48	21	0.0336	RED
21	48	23	0.1265	GREEN
21	48	33	0.1473	CYAN
21	48	41	0.0578	RED
21	48	45	0.1400	CYAN
21	48	49	0.2655	CYAN
21	48	51	0.0856	BLUE
21	48	61	0.1080	GREEN
21	48	95	0.1249	GREEN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
21	48	115	0.1559	CYAN
21	48	121	0.0874	BLUE
21	48	157	0.0703	BLUE
21	48	165	0.1361	CYAN
21	48	177	0.0985	BLUE
21	48	191	0.1042	GREEN
21	48	215	0.1088	GREEN
21	48	235	0.1207	GREEN
21	48	251	0.1051	GREEN
21	48	263	0.1302	CYAN
21	48	293	0.0662	BLUE
21	48	303	0.1113	GREEN
21	48	331	0.0867	BLUE
21	48	335	0.1330	CYAN
21	48	369	0.1421	CYAN
21	48	375	0.1220	GREEN
21	48	395	0.1016	GREEN
21	48	447	0.1165	GREEN
21	48	483	0.1062	GREEN
21	48	489	0.1074	GREEN
21	48	507	0.0744	BLUE
41	17	3	0.0487	CYAN
41	17	9	0.0003	GREEN
41	17	11	-0.1465	RED
41	17	13	0.0305	CYAN
41	17	17	-0.0277	GREEN
41	17	23	-0.0073	GREEN
41	17	29	-0.1112	RED
41	17	31	0.0007	GREEN
41	17	37	-0.1535	RED
41	17	43	-0.0503	BLUE
41	17	45	-0.1336	RED
41	17	47	0.0496	CYAN
41	17	49	-0.0149	GREEN
41	17	59	0.0380	CYAN
41	17	61	-0.0105	GREEN
41	17	63	-0.1189	RED
41	17	75	-0.0728	BLUE
41	17	85	-0.0304	GREEN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
41	17	89	-0.0387	BLUE
41	17	95	-0.0974	RED
41	17	99	-0.0986	RED
41	17	103	-0.1419	RED
41	17	109	-0.0588	BLUE
41	17	111	-0.0260	GREEN
41	17	113	-0.1665	RED
41	17	115	-0.2095	RED
41	17	119	0.0077	GREEN
41	17	123	-0.1554	RED
41	17	129	-0.1127	RED
41	17	137	-0.0938	RED
41	17	139	-0.1473	RED
41	17	143	-0.1050	RED
41	17	149	-0.0087	GREEN
41	17	155	-0.1380	RED
41	17	157	0.0348	CYAN
41	17	159	-0.0144	GREEN
41	17	169	0.0147	GREEN
41	17	175	-0.1393	RED
41	17	189	0.0259	CYAN
41	17	191	0.0419	CYAN
41	17	201	-0.0026	GREEN
41	18	3	-0.0042	GREEN
41	18	5	0.0027	GREEN
41	18	7	-0.1176	RED
41	18	9	0.0179	GREEN
41	18	13	0.0398	CYAN
41	18	17	-0.1153	RED
41	18	19	0.0302	CYAN
41	18	25	0.0519	CYAN
41	18	27	0.0161	GREEN
41	18	29	0.0488	CYAN
41	18	31	-0.0370	BLUE
41	18	37	0.0451	CYAN
41	18	39	-0.0465	BLUE
41	18	41	-0.0748	BLUE
41	18	43	0.0515	CYAN
41	18	53	-0.0472	BLUE

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
41	18	59	-0.0894	BLUE
41	18	61	0.0449	CYAN
41	18	65	-0.0612	BLUE
41	18	73	-0.0582	BLUE
41	18	77	0.0226	GREEN
41	18	79	0.0591	CYAN
41	18	83	0.0470	CYAN
41	18	87	0.0023	GREEN
41	18	91	-0.0116	GREEN
41	18	101	0.0501	CYAN
41	18	103	-0.1211	RED
41	18	107	-0.0782	BLUE
41	18	109	0.0101	GREEN
41	18	121	0.0431	CYAN
41	18	123	0.0423	CYAN
41	18	127	-0.0209	GREEN
41	18	129	0.0466	CYAN
41	18	131	-0.0469	BLUE
41	18	139	-0.0652	BLUE
41	18	147	0.0065	GREEN
41	18	151	0.0291	CYAN
41	18	153	0.0474	CYAN
41	18	169	-0.0423	BLUE
41	18	171	-0.0241	GREEN
41	18	175	0.0557	CYAN
41	18	177	-0.0168	GREEN
41	18	179	0.0000	GREEN
41	19	1	-0.0494	BLUE
41	19	5	-0.0803	BLUE
41	19	19	-0.0541	BLUE
41	19	21	-0.1353	RED
41	19	31	-0.0889	BLUE
41	19	39	0.0413	CYAN
41	19	41	-0.0854	BLUE
41	19	53	0.0482	CYAN
41	19	67	-0.0353	BLUE
41	19	71	0.0236	GREEN
41	19	75	-0.1825	RED
41	19	77	-0.0486	BLUE

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
41	19	83	-0.1475	RED
41	19	99	-0.1324	RED
41	19	101	0.0177	GREEN
41	19	103	-0.0363	BLUE
41	19	109	-0.1019	RED
41	19	113	-0.1032	RED
41	19	121	0.0285	CYAN
41	19	127	-0.1586	RED
41	19	129	-0.0130	GREEN
41	19	131	-0.0674	BLUE
41	19	147	-0.0922	RED
41	19	149	-0.1082	RED
41	19	153	-0.1039	RED
41	19	156	-0.0158	GREEN
41	19	161	-0.0441	BLUE
41	19	165	-0.0714	BLUE
41	19	171	-0.0808	BLUE
41	19	175	0.0459	CYAN
41	19	177	0.0316	CYAN
41	19	181	0.0310	CYAN
41	19	185	0.0486	CYAN
41	19	189	-0.0829	BLUE
41	19	193	-0.0437	BLUE
41	19	195	-0.0830	BLUE
41	19	197	-0.0558	BLUE
81	17	1	0.0926	GREEN
81	17	1	0.0926	GREEN
81	17	1	0.0926	GREEN
81	17	3	0.1705	CYAN
81	17	3	0.1705	CYAN
81	17	3	0.1705	CYAN
81	17	5	0.1203	CYAN
81	17	5	0.1203	CYAN
81	17	5	0.1203	CYAN
81	17	7	0.0395	BLUE
81	17	7	0.0395	BLUE
81	17	9	0.1086	CYAN
81	17	9	0.1086	CYAN
81	17	9	0.1086	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	17	11	0.0102	RED
81	17	13	0.1254	CYAN
81	17	13	0.1254	CYAN
81	17	13	0.1254	CYAN
81	17	15	0.0089	RED
81	17	15	0.0089	RED
81	17	17	0.0496	BLUE
81	17	19	-0.0523	RED
81	17	21	-0.0311	RED
81	17	21	-0.0311	RED
81	17	23	0.0607	BLUE
81	17	23	0.0607	BLUE
81	17	23	0.0607	BLUE
81	17	25	0.1282	CYAN
81	17	25	0.1282	CYAN
81	17	25	0.1282	CYAN
81	17	27	0.1264	CYAN
81	17	27	0.1264	CYAN
81	17	27	0.1264	CYAN
81	17	29	-0.0143	RED
81	17	31	0.1223	CYAN
81	17	31	0.1223	CYAN
81	17	31	0.1223	CYAN
81	17	33	0.1049	GREEN
81	17	33	0.1049	GREEN
81	17	33	0.1049	GREEN
81	17	35	0.0210	BLUE
81	17	35	0.0210	BLUE
81	17	37	-0.0069	RED
81	17	39	-0.0689	RED
81	17	41	-0.0326	RED
81	17	43	0.0533	BLUE
81	17	45	-0.0267	RED
81	17	45	-0.0267	RED
81	17	47	0.1440	CYAN
81	17	47	0.1440	CYAN
81	17	47	0.1440	CYAN
81	17	49	0.0713	BLUE
81	17	49	0.0713	BLUE

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	17	49	0.0713	BLUE
81	17	51	0.1117	CYAN
81	17	51	0.1117	CYAN
81	17	51	0.1117	CYAN
81	17	53	0.0142	BLUE
81	17	55	0.1743	CYAN
81	17	55	0.1743	CYAN
81	17	55	0.1743	CYAN
81	17	57	0.0561	BLUE
81	17	57	0.0561	BLUE
81	17	59	0.1754	CYAN
81	17	59	0.1754	CYAN
81	17	59	0.1754	CYAN
81	17	61	0.0837	GREEN
81	17	61	0.0837	GREEN
81	17	61	0.0837	GREEN
81	17	63	-0.0142	RED
81	17	63	-0.0142	RED
81	17	65	0.1455	CYAN
81	17	65	0.1455	CYAN
81	17	65	0.1455	CYAN
81	17	67	0.0728	BLUE
81	17	67	0.0728	BLUE
81	17	67	0.0728	BLUE
81	17	69	0.1227	CYAN
81	17	69	0.1227	CYAN
81	17	69	0.1227	CYAN
81	17	71	0.0812	GREEN
81	17	71	0.0812	GREEN
81	17	71	0.0812	GREEN
81	17	73	0.0231	BLUE
81	17	73	0.0231	BLUE
81	17	75	-0.0304	RED
81	17	77	0.1735	CYAN
81	17	77	0.1735	CYAN
81	17	77	0.1735	CYAN
81	17	79	0.0822	GREEN
81	17	79	0.0822	GREEN
81	17	79	0.0822	GREEN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	17	81	0.1450	CYAN
81	17	81	0.1450	CYAN
81	17	81	0.1450	CYAN
81	17	83	0.0699	BLUE
81	17	83	0.0699	BLUE
81	17	83	0.0699	BLUE
81	17	85	0.0734	BLUE
81	17	85	0.0734	BLUE
81	17	85	0.0734	BLUE
81	17	87	0.1426	CYAN
81	17	87	0.1426	CYAN
81	17	87	0.1426	CYAN
81	17	89	0.0643	BLUE
81	17	89	0.0643	BLUE
81	17	89	0.0643	BLUE
81	17	91	-0.0022	RED
81	17	93	0.0144	BLUE
81	17	93	0.0144	BLUE
81	17	95	0.0093	RED
81	17	95	0.0093	RED
81	17	97	0.1388	CYAN
81	17	97	0.1388	CYAN
81	17	97	0.1388	CYAN
81	17	99	0.0123	RED
81	17	101	0.1304	CYAN
81	17	101	0.1304	CYAN
81	17	101	0.1304	CYAN
81	17	103	0.0167	BLUE
81	17	105	-0.0292	RED
81	17	105	-0.0292	RED
81	17	107	-0.0289	RED
81	17	109	0.0278	BLUE
81	17	111	0.0867	GREEN
81	17	111	0.0867	GREEN
81	17	111	0.0867	GREEN
81	17	113	-0.0311	RED
81	17	115	-0.0573	RED
81	17	117	0.0425	BLUE
81	17	117	0.0425	BLUE

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	17	119	0.1183	CYAN
81	17	119	0.1183	CYAN
81	17	119	0.1183	CYAN
81	17	121	0.1244	CYAN
81	17	121	0.1244	CYAN
81	17	121	0.1244	CYAN
81	17	123	-0.0313	RED
81	17	123	-0.0313	RED
81	17	125	0.0880	GREEN
81	17	125	0.0880	GREEN
81	17	125	0.0880	GREEN
81	17	127	0.1500	CYAN
81	17	127	0.1500	CYAN
81	17	127	0.1500	CYAN
81	17	129	0.0116	RED
81	17	131	0.0514	BLUE
81	17	131	0.0514	BLUE
81	17	133	0.1330	CYAN
81	17	133	0.1330	CYAN
81	17	133	0.1330	CYAN
81	17	135	0.0369	BLUE
81	17	137	0.0276	BLUE
81	17	137	0.0276	BLUE
81	17	139	-0.0474	RED
81	17	141	0.0368	BLUE
81	17	141	0.0368	BLUE
81	17	143	0.0046	RED
81	17	145	0.1407	CYAN
81	17	145	0.1407	CYAN
81	17	145	0.1407	CYAN
81	17	147	-0.0570	RED
81	17	149	0.0934	GREEN
81	17	149	0.0934	GREEN
81	17	149	0.0934	GREEN
81	17	151	0.1217	CYAN
81	17	151	0.1217	CYAN
81	17	151	0.1217	CYAN
81	17	153	0.1741	CYAN
81	17	153	0.1741	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	17	153	0.1741	CYAN
81	17	155	-0.0152	RED
81	17	157	0.1285	CYAN
81	17	157	0.1285	CYAN
81	17	157	0.1285	CYAN
81	17	159	0.1015	GREEN
81	17	159	0.1015	GREEN
81	17	159	0.1015	GREEN
81	17	161	0.0482	BLUE
81	17	161	0.0482	BLUE
81	17	163	0.1094	CYAN
81	17	163	0.1094	CYAN
81	17	163	0.1094	CYAN
81	17	165	0.1725	CYAN
81	17	165	0.1725	CYAN
81	17	165	0.1725	CYAN
81	17	167	-0.0233	RED
81	17	167	-0.0233	RED
81	17	169	0.0779	GREEN
81	17	169	0.0779	GREEN
81	17	169	0.0779	GREEN
81	17	171	0.0900	GREEN
81	17	171	0.0900	GREEN
81	17	171	0.0900	GREEN
81	17	173	-0.0023	RED
81	17	173	-0.0023	RED
81	17	175	-0.0190	RED
81	17	175	-0.0190	RED
81	17	177	0.1113	CYAN
81	17	177	0.1113	CYAN
81	17	177	0.1113	CYAN
81	17	179	0.0157	BLUE
81	17	179	0.0157	BLUE
81	17	181	0.1757	CYAN
81	17	181	0.1757	CYAN
81	17	181	0.1757	CYAN
81	17	183	-0.0180	RED
81	17	185	0.1350	CYAN
81	17	185	0.1350	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	17	185	0.1350	CYAN
81	17	187	0.0153	BLUE
81	17	189	0.1385	CYAN
81	17	189	0.1385	CYAN
81	17	189	0.1385	CYAN
81	17	191	0.1588	CYAN
81	17	191	0.1588	CYAN
81	17	191	0.1588	CYAN
81	17	193	0.1427	CYAN
81	17	193	0.1427	CYAN
81	17	193	0.1427	CYAN
81	17	195	0.0700	BLUE
81	17	195	0.0700	BLUE
81	17	195	0.0700	BLUE
81	17	197	0.0247	BLUE
81	17	197	0.0247	BLUE
81	17	199	0.1733	CYAN
81	17	199	0.1733	CYAN
81	17	199	0.1733	CYAN
81	17	201	0.0809	GREEN
81	17	201	0.0809	GREEN
81	17	201	0.0809	GREEN
81	17	203	-0.0398	RED
81	18	1	0.0749	BLUE
81	18	1	0.0749	BLUE
81	18	1	0.0749	BLUE
81	18	3	0.1007	GREEN
81	18	3	0.1007	GREEN
81	18	3	0.1007	GREEN
81	18	5	0.0786	GREEN
81	18	5	0.0786	GREEN
81	18	5	0.0786	GREEN
81	18	7	-0.0265	RED
81	18	9	0.1114	CYAN
81	18	9	0.1114	CYAN
81	18	9	0.1114	CYAN
81	18	11	0.0190	BLUE
81	18	13	0.1391	CYAN
81	18	13	0.1391	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	18	13	0.1391	CYAN
81	18	15	0.0047	RED
81	18	15	0.0047	RED
81	18	17	0.0332	BLUE
81	18	19	0.1524	CYAN
81	18	19	0.1524	CYAN
81	18	19	0.1524	CYAN
81	18	21	0.1025	GREEN
81	18	21	0.1025	GREEN
81	18	21	0.1025	GREEN
81	18	23	0.0119	RED
81	18	23	0.0119	RED
81	18	25	0.1157	CYAN
81	18	25	0.1157	CYAN
81	18	25	0.1157	CYAN
81	18	27	0.1180	CYAN
81	18	27	0.1180	CYAN
81	18	27	0.1180	CYAN
81	18	29	0.1684	CYAN
81	18	29	0.1684	CYAN
81	18	29	0.1684	CYAN
81	18	31	0.0587	BLUE
81	18	31	0.0587	BLUE
81	18	31	0.0587	BLUE
81	18	33	0.1046	GREEN
81	18	33	0.1046	GREEN
81	18	33	0.1046	GREEN
81	18	35	0.0631	BLUE
81	18	35	0.0631	BLUE
81	18	35	0.0631	BLUE
81	18	37	0.1644	CYAN
81	18	37	0.1644	CYAN
81	18	37	0.1644	CYAN
81	18	39	0.1035	GREEN
81	18	39	0.1035	GREEN
81	18	39	0.1035	GREEN
81	18	41	0.0500	BLUE
81	18	43	0.1740	CYAN
81	18	43	0.1740	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	18	43	0.1740	CYAN
81	18	45	0.0500	BLUE
81	18	45	0.0500	BLUE
81	18	47	0.1294	CYAN
81	18	47	0.1294	CYAN
81	18	47	0.1294	CYAN
81	18	49	0.0342	BLUE
81	18	49	0.0342	BLUE
81	18	51	0.1402	CYAN
81	18	51	0.1402	CYAN
81	18	51	0.1402	CYAN
81	18	53	0.0817	GREEN
81	18	53	0.0817	GREEN
81	18	53	0.0817	GREEN
81	18	55	0.1546	CYAN
81	18	55	0.1546	CYAN
81	18	55	0.1546	CYAN
81	18	57	0.0012	RED
81	18	59	0.0198	BLUE
81	18	61	0.1569	CYAN
81	18	61	0.1569	CYAN
81	18	61	0.1569	CYAN
81	18	63	0.0354	BLUE
81	18	65	0.0496	BLUE
81	18	65	0.0496	BLUE
81	18	67	0.0043	RED
81	18	67	0.0043	RED
81	18	69	0.0797	GREEN
81	18	69	0.0797	GREEN
81	18	69	0.0797	GREEN
81	18	71	0.1689	CYAN
81	18	71	0.1689	CYAN
81	18	71	0.1689	CYAN
81	18	73	0.0187	BLUE
81	18	73	0.0187	BLUE
81	18	75	0.1194	CYAN
81	18	75	0.1194	CYAN
81	18	75	0.1194	CYAN
81	18	77	0.1790	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	18	77	0.1790	CYAN
81	18	77	0.1790	CYAN
81	18	79	0.1764	CYAN
81	18	79	0.1764	CYAN
81	18	79	0.1764	CYAN
81	18	81	0.0574	BLUE
81	18	81	0.0574	BLUE
81	18	81	0.0574	BLUE
81	18	83	0.1358	CYAN
81	18	83	0.1358	CYAN
81	18	83	0.1358	CYAN
81	18	85	0.0534	BLUE
81	18	87	0.1065	GREEN
81	18	87	0.1065	GREEN
81	18	87	0.1065	GREEN
81	18	89	0.0650	BLUE
81	18	89	0.0650	BLUE
81	18	89	0.0650	BLUE
81	18	91	0.0935	GREEN
81	18	91	0.0935	GREEN
81	18	91	0.0935	GREEN
81	18	93	0.1471	CYAN
81	18	93	0.1471	CYAN
81	18	93	0.1471	CYAN
81	18	95	0.0487	BLUE
81	18	95	0.0487	BLUE
81	18	97	0.0486	BLUE
81	18	99	0.0564	BLUE
81	18	99	0.0564	BLUE
81	18	99	0.0564	BLUE
81	18	101	0.1415	CYAN
81	18	101	0.1415	CYAN
81	18	101	0.1415	CYAN
81	18	103	0.0487	BLUE
81	18	105	0.1657	CYAN
81	18	105	0.1657	CYAN
81	18	105	0.1657	CYAN
81	18	107	0.0211	BLUE
81	18	109	0.1033	GREEN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	18	109	0.1033	GREEN
81	18	109	0.1033	GREEN
81	18	111	-0.0060	RED
81	18	111	-0.0060	RED
81	18	113	0.0969	GREEN
81	18	113	0.0969	GREEN
81	18	113	0.0969	GREEN
81	18	115	0.1807	CYAN
81	18	115	0.1807	CYAN
81	18	115	0.1807	CYAN
81	18	117	0.1638	CYAN
81	18	117	0.1638	CYAN
81	18	117	0.1638	CYAN
81	18	119	0.1453	CYAN
81	18	119	0.1453	CYAN
81	18	119	0.1453	CYAN
81	18	121	0.1284	CYAN
81	18	121	0.1284	CYAN
81	18	121	0.1284	CYAN
81	18	123	0.1573	CYAN
81	18	123	0.1573	CYAN
81	18	123	0.1573	CYAN
81	18	125	0.1476	CYAN
81	18	125	0.1476	CYAN
81	18	125	0.1476	CYAN
81	18	127	0.0775	GREEN
81	18	127	0.0775	GREEN
81	18	127	0.0775	GREEN
81	18	129	0.1577	CYAN
81	18	129	0.1577	CYAN
81	18	129	0.1577	CYAN
81	18	131	0.0644	BLUE
81	18	131	0.0644	BLUE
81	18	131	0.0644	BLUE
81	18	135	0.0730	BLUE
81	18	135	0.0730	BLUE
81	18	135	0.0730	BLUE
81	18	137	0.1397	CYAN
81	18	137	0.1397	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	18	137	0.1397	CYAN
81	18	139	0.0312	BLUE
81	18	139	0.0312	BLUE
81	18	141	0.1310	CYAN
81	18	141	0.1310	CYAN
81	18	141	0.1310	CYAN
81	18	143	0.1676	CYAN
81	18	143	0.1676	CYAN
81	18	143	0.1676	CYAN
81	18	145	0.0521	BLUE
81	18	145	0.0521	BLUE
81	18	147	0.1588	CYAN
81	18	147	0.1588	CYAN
81	18	147	0.1588	CYAN
81	18	149	0.1299	CYAN
81	18	149	0.1299	CYAN
81	18	149	0.1299	CYAN
81	18	151	0.1127	CYAN
81	18	151	0.1127	CYAN
81	18	151	0.1127	CYAN
81	18	153	0.1263	CYAN
81	18	153	0.1263	CYAN
81	18	153	0.1263	CYAN
81	18	155	0.1743	CYAN
81	18	155	0.1743	CYAN
81	18	155	0.1743	CYAN
81	18	157	0.0579	BLUE
81	18	157	0.0579	BLUE
81	18	157	0.0579	BLUE
81	18	159	0.0054	RED
81	18	159	0.0054	RED
81	18	161	0.0473	BLUE
81	18	163	0.1315	CYAN
81	18	163	0.1315	CYAN
81	18	163	0.1315	CYAN
81	18	165	0.1367	CYAN
81	18	165	0.1367	CYAN
81	18	165	0.1367	CYAN
81	18	167	0.1535	CYAN

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	18	167	0.1535	CYAN
81	18	167	0.1535	CYAN
81	18	169	0.0619	BLUE
81	18	169	0.0619	BLUE
81	18	169	0.0619	BLUE
81	18	171	0.0533	BLUE
81	18	171	0.0533	BLUE
81	18	171	0.0533	BLUE
81	18	173	0.1597	CYAN
81	18	173	0.1597	CYAN
81	18	173	0.1597	CYAN
81	18	175	0.1742	CYAN
81	18	175	0.1742	CYAN
81	18	175	0.1742	CYAN
81	18	177	0.0639	BLUE
81	18	177	0.0639	BLUE
81	18	177	0.0639	BLUE
81	18	179	0.0638	BLUE
81	18	179	0.0638	BLUE
81	18	179	0.0638	BLUE
81	18	181	0.0184	BLUE
81	18	183	0.0855	GREEN
81	18	183	0.0855	GREEN
81	18	183	0.0855	GREEN
81	19	3	0.1055	GREEN
81	19	5	0.0013	RED
81	19	7	0.1384	CYAN
81	19	11	-0.0684	RED
81	19	13	-0.0472	RED
81	19	35	-0.0700	RED
81	19	39	0.1606	CYAN
81	19	45	-0.0309	RED
81	19	49	-0.0366	RED
81	19	51	0.1132	CYAN
81	19	53	0.1618	CYAN
81	19	59	-0.0414	RED
81	19	65	-0.0251	RED
81	19	71	0.0950	GREEN
81	19	77	0.0184	BLUE

Crop Code	State FIPS	County Code	Proportional Difference at 75% Coverage	Map Color
81	19	83	-0.0590	RED
81	19	85	0.0614	BLUE
81	19	87	0.0260	BLUE
81	19	95	0.0533	BLUE
81	19	101	0.0628	BLUE
81	19	103	0.0105	RED
81	19	105	-0.0556	RED
81	19	107	0.0308	BLUE
81	19	109	-0.0651	RED
81	19	111	0.0466	BLUE
81	19	113	-0.0334	RED
81	19	117	0.1401	CYAN
81	19	121	0.0741	BLUE
81	19	123	-0.0159	RED
81	19	125	0.0326	BLUE
81	19	131	0.0197	BLUE
81	19	133	0.0822	GREEN
81	19	135	0.1348	CYAN
81	19	137	0.0627	BLUE
81	19	141	-0.0496	RED
81	19	145	0.0621	BLUE
81	19	151	-0.0146	RED
81	19	153	-0.0256	RED
81	19	155	-0.0106	RED
81	19	159	0.1384	CYAN
81	19	171	-0.0262	RED
81	19	173	0.1458	CYAN
81	19	175	0.1055	GREEN
81	19	177	0.1378	CYAN
81	19	179	0.0206	BLUE
81	19	181	0.1048	GREEN
81	19	183	0.0008	RED
81	19	185	0.1476	CYAN
81	19	189	-0.0245	RED
81	19	191	0.0139	BLUE
81	19	193	0.0812	GREEN
81	19	195	-0.0080	RED